Does Shareholder Overlap Alleviate Patent Holdup?

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Abstract

When innovation is cumulative, patent protection on early inventions can generate holdup problems if later complementary patents are owned by different firms. We show that shareholder ownership overlap across firms with patent complementarities helps mitigate such holdup problems and correlates significantly with higher R&D investment, more patent success, and lower patent infringement litigation risk for firms with follow-on innovations. The positive innovation effect is stronger for concentrated overlapping ownership and when overlapping shareholders are dedicated investors, with long investment horizons and underdiversified portfolios.

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1 Introduction

New technological discoveries typically form part of a cumulative innovation process, in which later innovations build on a foundation provided by early innovators. Consequently, patent protection on early inventions implies that the full economic value of a later innovation might be unlocked only if the downstream (i.e., later) innovator can simultaneously secure access to many complementary upstream patents.[1] By law, when a follow-on product from the later innovator uses features that fall within the scope of protection of the first innovation, the second-generation innovator must obtain a license from the first-generation innovator, or risk being sued for patent infringement.[2] Viewed from this perspective, patent processes generate holdup problems for follow-on innovators if they have to make specific investments and ex-ante contracting on licenses is infeasible.[3]

In this paper, we study if overlapping (or common) institutional ownership can provide holdup relief. We measure ownership overlap specifically between a downstream firm with patent options and an upstream firm owning complementary patents already granted.[4] From the property rights perspective of a firm (Grossman and Hart, 1986; Hart and Moore, 1990; Hart, 1995), such shareholder overlap should *extend the effective boundary of the downstream firm* — allowing potentially for the internalization of patent conflicts in the absence of efficient ex-ante contracting. Yet, to our knowledge, no systematic empirical evidence exists that would validate the holdup attenuation effect of (institutional) shareholder overlap.

This paper seeks to fill this gap by asking the following research questions: (i) Is there a positive causal effect from institutional shareholder overlap on the success of a patent if the overlap is between the firm that owns the patent and an upstream firm that owns a precursory complementary patent? (ii) Do firm-level measures of such specific shareholder overlap (which presumably alleviating holdup) covary in an economically significant manner with input and output mea-

[1] Follow-on inventions can still be patented, but they cannot be worked for *commercial* purposes if the follow-on products infringe on the patent rights of the earlier inventions. This situation is also referred to as patent thicket, see Shapiro (2001).

[2] Lanjouw and Schankerman (2001) find evidence that upstream firms often file lawsuits to protect patents that form the base of a cumulative chain in order to extract rents from subsequent follow-on inventions.

[3] Ex-ante contracting prior to specific investments is not feasible for the second-generation innovator in that such contracting risks leaking valuable information about developement options to a potential competitor.

[4] The terms up- and downstream refer to the time line or time flow of the patent approval process. The upstream firm is the one owning a precursory patent and the downstream firm pursues a follow-up patent.

sures of patent production, namely R&D investment, the number of approved patents, and patent citations on approved patents? (iii) Is the holdup attenuation achieved more effectively if the institutional overlap is constituted by "activist" investors and if this overlap is concentrated among a few overlapping institutional investors?

We provide three new empirical results in support of the holdup attenuation hypothesis of institutional ownership. First, we present causal evidence based on a quasi-natural experiment where patent-level shareholder overlap increases exogenously due to a merger of financial institutions. Based on 50 mergers of financial institutions in the period 1991–2006, we examine merging institutions' portfolio firms reported in the calendar quarter-end before merger completion dates and identify their patents filed by these portfolio firms in an eight-year event window around merger completion years. Of the identified patents, we obtain $11,112$ treated patents for which the institutional mergers generate a significant increase in shareholder overlap between the downstream firms that own these patents and the upstream firms that own the complementary patents. We next carry out a matching procedure that selects control patents from the same merger event and year with no increase in shareholder overlap through the financial institution mergers. We employ a difference-in-difference approach to compare the success of treated and control patents around the financial institution merger event. By construction, the patent-level shareholder overlap (sol) for upstream firms increases for treated patents (relative to control patents) in the years after the merger by 1.8 percentage points, which amounts to 12.08% of its standard deviation. At the same time, the forward citation count of treated patents filed post-merger increases by 12.6% relative to the control patents. The quasi-natural experiment suggests a causal link between shareholder overlap and increased patent success through holdup attenuation.

After establishing a causal link between shareholder overlap and patent success, we broaden our analysis in a second step based on the full sample of U.S. listed firms with patents. The firm-level evidence shows an economically and statistically significant relationship between a firm's patent success and the average shareholder overlap (SOL) with firms controlling precursory patents. This strong relationship extends to both the extensive margin (patent-count based) and intensive margin (citation-count based) of patent production. Placebo tests show that this positive relationship only exists if shareholder overlap is calculated for the correct firm pairs matching the patent citation link from the downstream to the upstream patent. The positive relationship between patent success and shareholder overlap is matched by a strong positive correlation between R&D investment and shareholder overlap. Moreover, decomposing institutional ownership into a component delivering shareholder overlap and the residual component of (pure) institutional ownership *per se* shows that the former and not the latter matters as a positive covariant of firms' R&D investment. Hence, the firm evidence does not support the idea that institutional ownership *per se* is conducive to R&D investment (Aghion, Van Reenen, and Zingales, 2013). To further pinpoint that the holdup attenuation is the working mechanism, we seek additional evidence on patent litigations. We show that a one-standard-deviation increase in shareholder overlap with firms owning precursory patents is associated *ceteris paribus* with a 10.5% reduction in the patent litigation risk of the downstream innovating firms in our sample.

Third, we explore the heterogeneous transmission of ownership interests to firm outcomes. Following McCahery, Sautner, and Starks (2016), we define dedicated institutional shareholders as those with a long investment horizon (i.e., low turnover) and low asset diversification—thus excluding index funds. For dedicated shareholders we find a three times stronger economic link between their ownership overlap with upstream firms controlling precursory patents and various measures of the patent success of downstream firms. The coordination problem between multiple overlapping shareholders should also constrain shareholder power. We find that a Herfindahl-Hirschman Index capturing the dispersion of the overlapping ownership has additional negative explanatory power for the patent success of downstream firms—suggesting that coordination among dispersed overlapping investors indeed weakens their collective power.

A first major challenge in addressing our research question is the identification of holdup situations. Here we build on Galasso and Schankerman (2015), and use patent citation links with upstream firms to proxy for the potential patent holdup risk faced by a downstream firm. To further support this identification, we seek additional evidence that such citation links do indeed proxy for potential patent holdup. Using patent litigation data from the Public Access to Court Electronic Records (PACER), Figure 1, Panel A, shows that intra-industry firm pairs with patent citation links are on average 15 times as likely to engage in patent-related lawsuits against each other as those intra-industry firm pairs without any citation links. For pharmaceutical firms, we are able to obtain their licensing deals and royalty transfer information from the Cortellis database.[5] Panels B and C in Figure 1 show that firm pairs with citation links feature 17.9 times more licensing deals and 43.6 times more royalty transfer between each other than firm pairs without citation links. Overall, the data on patent litigation, licensing deals, and royalty transfer support the argument that patent citation links represent a reasonable proxy for asset complementarity and patent holdup risk.

The extent to which overlapping institutional investors influence corporate policy is subject to debate. Institutional investors may not always have the operational knowledge and incentive to influence or coordinate specific product market decisions among their portfolio firms. However, patent holdup and potential patent litigation among portfolio firms represent particular situations with high economic stakes that invite active fund governance. Anecdotal evidence on the behaviors of institutional investors supports this view. For example Albert J. Wilson, Vice President and Secretary of TIAA-CREF, noted in a public speech that given his fund's joint ownership in both sides of the litigation cases of Pennzoil vs. Texaco and Apple vs. Microsoft, his fund was able to apply pressure on the litigants to speed up their conflict resolution (Hansen and Lott, 1996). Shekita (2020) provides a list of 30 specific cases on public record in which overlapping institutional shareholders exercise influence on firm decisions. Solomon and Soltes (2015) provide evidence that private meetings between top firm executives and institutional investors are pervasive: Based on the meeting schedule of top executives in a representative mid-cap, NYSE traded firm, they document over 900 private meetings of the firm's executives with 340 different institutional investors over 6 years. Unsurprisingly, such meetings are more frequent if investors hold a larger share of the firm's equity. Accordingly, we expect the size of the overlapping investment share, the investor type (i.e., active versus passive), and the concentration of cross-ownership in few investors to matter for the conjectured holdup attenuation effects.

The role of institutional ownership and its effect on intra-industry competition has recently

[5] Our analysis includes only the licensing deals for which both the licensor and licensee are included in the CRSP database. The final sample comprises a total of $1,238$ licensing deals for the period 1991–2007. We count the number of licensing deals in which the licensee cited the licensor in the past three years. We then calculate the aggregate royalties in these deals. We also count the number of licensing deals and royalty value for firm pairs without any citation links in the past three years. Although royalties generally increase with the importance of a patent (Sichelman, 2018), the Cortellis database does not indicate which exact patent(s) is (are) covered in each licensing deal.

evolved into a major policy debate because of the long-run trend in growth of such ownership and parallel evidence of increased profit margins in various industries (Azar, Raina, and Schmalz, 2019; Azar, Schmalz, and Tecu, 2018; Gutiérrez and Philippon, 2017; He and Huang, 2017; Koch, Panayides, and Thomas, 2020). Our paper approaches this controversy from a new angle: We condition our analysis on situations of potential patent conflict in which extension of the firm boundary through very specific cross-ownership is socially beneficial and implies more investment in patents. By contrast, most previous work on institutional cross-ownership has not been concerned with the *particular nature of the inter-firm relationship* and tests for generic anti-competitive effects revealed in larger producer rents and less investment. Our conditional analysis has three major advantages: First, it increases the statistical power to detect economic effects of common ownership by focusing on potential holdup situations with high economic stakes. Second, the predicted effects of common ownership on investment and patent success are unambiguous and go in the opposite direction of what theories of product market collusion predict. Third, the *high specificity of patent links* on which cross-ownership operates allows us to design falsification/placebo tests not available in a setting with generic anti-competitive effects at the industry level.

Some previous inferences about financial institution mergers as a quasi-experiment have encountered criticism that does not apply to our setting. Lewellen and Lowry (2020) question the validity of causal inference on firm performance in He and Huang (2017) because of the clustering of treated firm observations in the years 2008 and 2009 in the financial institution merger sample. They argue that the post-crisis recovery by growth firms combined with imperfectly matched control firms distorts the inference. We do not use financial institution merger events from the problematic the crisis years. Importantly, our causal analysis is at the patent level and we compare control and treated patents filed by the same firm in the same year—making it a within-firm analysis that circumvents issues of control firm matching.

We highlight that holdup resolution through mergers, anti-trust law and enforcement, or simple ex-ante contracting on patent access (i.e. licensing) all faces different obstacles not encountered by institutional shareholder overlap. Firm mergers entail high transactional costs (Bena and Li, 2014; Creighton and Sher, 2009). In cases when an upstream patent is complementary to multiple downstream firms and their patents, consolidating any one of the downstream firms with the upstream firm does not solve the holdup problem for the remaining downstream firms, and might actually accentuate anti-trust concerns. Reducing holdup through standard setting and/or anti-trust enforcement are contentious processes of uncertain outcome (Shapiro, 2020). Finally, ex-ante contracting is difficult in patent races where patent development ideas are private knowledge and need to be shielded from competitors. Even if a downstream firm anticipates that it needs access to a complementary patent of an upstream firm to realize the full value of a prospective patent, it still may not want to engage in ex-ante contracting for fear that its patent idea could be exploited by the competitor. Ex-ante contracting risks dissipating highly valuable information about development opportunities that can exceed the gains from a stronger negotiation position on rents before specific investments are sunk.

For many years, US anti-trust law and policy on patent holdup has been a battleground for vested interests with high economic stakes. This has polarized the debate to a point where the existence of patent holdup as an economically significant problem is called into question.[6] Our evidence that the success of follow-up patents is strongly conditioned by institutional shareholder overlap is hard to reconcile with such a position. To the extent that our holdup identification is imperfect (i.e., patent citation links is only a proxy for potential holdup) and institutional shareholder overlap falls short of full alignment of interests (like in a merger), our estimates represent only a lower bound for the adverse economic effects of patent holdup on follow-up patents.

Our paper continues as follows. Section 2 surveys the related literature, and Section 3 describes the data. Section 4 provides the causal evidence based on financial institution mergers as a quasi-experiment. Section 5 examines the full sample of U.S. patent-owning firms for consistency with the holdup attenuation hypothesis of institutional ownership. Section 6 studies the transmission mechanism by differentiating between different types of institutional ownership and their concentration. More robustness considerations follow in Section 7. Section 8 concludes.

[6]Under the Trump adminstration, the Department of Justice (DOJ) led by Assistant Attorney General Delrahim has reversed previous anti-trust policy and supported patent rights owners against standard-setting organizations (SSO) that promote access to standard essential patents (SEPs) on fair, reasonable, and non-discriminatory (FRAND) terms. See Shapiro and Lemley (2020, pages 36-39) for details.

2 Related Literature

Our paper is situated at the intersection of three strands of literature; namely on (i) the determinants of patent innovation and patent success; (ii) optimal property rights in situations of incomplete contracting and the role of patent holdup; and (iii) the real effects of institutional cross-ownership.

First, the early literature on cumulative (or sequential) innovation emphasizes a positive externality of early innovators on later innovators via knowledge spillover (e.g., D'Aspremont and Jacquemin, 1988). A seminal paper by Green and Scotchmer (1995) argues that in a perfect contracting environment, ex-ante licenses are optimal and will be negotiated. In their framework, efficient bargaining ensures that upstream patent rights do not impede follow-on innovation. More recent studies (e.g., Heller and Eisenberg, 1998), however, argue that various transaction costs exist and can result in inefficient bargaining and patent holdup risk for downstream innovators. Bargaining failure due to information asymmetry (Bessen and Maskin 2009; Galasso and Schankerman 2015) and/or excessive royalty stacking (Galasso and Schankerman, 2010) can even block follow-on innovation completely. Empirically, Murray and Stern (2007), Williams (2013), and Galasso and Schankerman (2015) find evidence that patent holdup reduces downstream research and development by about 10% to 50%. Lanjouw and Schankerman (2001) further document the litigation risk faced by downstream innovators as upstream patent owners try to maximize their overall patent rents. In particular, upstream firms are more likely to file infringement lawsuits to protect patents that form the base of a cumulative chain and patents that are cited by more follow-on patentees. Our paper contributes to this empirical literature on the corporate innovation process and represents (to our knowledge) the most comprehensive empirical study on potential holdup risk.

Second, the property rights literature (Grossman and Hart, 1986; Hart and Moore, 1990; Hart, 1995) suggests that joint asset ownership attenuates holdup problems under conditions of asset specificity and ex-ante incomplete contracting. In the case of cumulative innovation, the first condition (i.e., asset specificity) is fulfilled for many new downstream patents because by law a downstream innovating firm must license upstream patents before it can market its follow-on (or second generation) products that use features under the IP protection of upstream patents. The second condition (ex-ante incomplete contracting) is also fulfilled. Various contingencies can arise during an innovation process. Unforeseen outcomes of any innovation project make it impossible for an innovating firm to write an ex-ante complete contract. The difficulty of ex-ante contracting is further compounded by the requirement for secrecy: Disclosure of private information about the patent opportunity in ex-ante license negotiation invites rival patent pursuit. The need for ex-post negotiation thus creates a patent holdup problem for the downstream firm after specific investments are sunk.

Notwithstanding its prominence in economic theory, the property rights view of firm boundaries has seen few empirical applications. A variety of empirical problems explains the scarcity of evidence. First, *non-contractible holdup problems* are often difficult to identify in a complicated business environment. Second, *underinvestment at the project level* requires a level of data disaggregation typically not available from corporate investment data, and any firm-level analysis is clouded by the fact that a firm can shift investments to other projects for which holdup problems are less severe. Third, investments may involve intangible resources (such as managerial attention), which pose additional *measurement problems* for empirical analyses. Patent data are particularly suited to addressing these issues. First, they allow the identification of potential holdup risk directly through the explicit citation of precursory patents in patent filings. Though imperfect, this identification idea pinpoints a large set of firm pairs where bilateral patent conflict is latent. Second, we can infer (latent) *within firm* underinvestment in specific patent projects from the diminished success of the patent captured by future patent citations. Aggregate firm-level investment in innovation can be inferred directly from the reported firm-level R&D expenditure (or indirectly from the aggregate success of all patents filed by a firm).

Third, our work relates to a growing literature on the real effect of institutional cross-firm (or overlapping) ownership. Since Rubinstein and Yaari (1983) and Rotemberg (1984), a number of theoretical studies have argued that overlapping shareholders might coordinate to reduce competition in product markets. The increasing economic significance of institutional ownership has fostered an interest in this channel. Some recent industry studies provide evidence consistent with the anti-competitive argument. For example, Azar *et al.* (2018) suggest that overlapping ownership softens product market competition in the U.S. airline industry. Similar evidence is also documented by Aslan (2019) for the consumer goods industry by, Azar *et al.* (2019) for the banking industry, and by Newham, Seldeslachts, and Estañol (2019) and Gerakos and Xie (2019) for the pharmaceutical industry. He and Huang (2017) also show that large overlapping shareholders facilitate product market collaboration among their portfolio firms in the same industry, and that these firms experience greater profitability and market share growth.[7] He, Xia, and Zhao (2020) show that during corporate litigation, media companies that share common institutional ownership with the defendant provide more favorable news coverage of the defendant and allow common owners to exit at more favorable prices. Two recent studies demonstrate that overlapping ownership also matters for startups. Using project-level data, Li, Liu, and Taylor (2020) document that, under some circumstances, common venture capitalists stifle the competition among jointly owned startups by discontinuing the competing project of the lagging startup. Eldar, Grennan, and Waldock (2020) find that common venture capitalists contribute to startup growth by facilitating information exchange and efficient opportunity allocation among their commonly owned startups. By contrast, Koch, Panayides, and Thomas (2020) question any general aggregate link between overlapping shareholder ownership and industry profitability.[8] While broad evidence beyond a particular industry is desirable, research progress is most likely to come from a more conditional analysis that accounts for the specific firm pair problem on which cross-ownership imprints a potential effect. Our focus on patent holdup represents such a conditional analysis.

Our causal evidence on the role of shareholder overlap draws on He and Huang (2017)'s idea that mergers of financial institutions represent a quasi-natural experiment for an exogenous increase of such overlap. Lewellen and Lowry (2020) argue that their merger sample features a clustering of treated firm observations in the years 2008-9, and an imperfectly matched control sample of firms. This critique does not apply to our analysis since we do not use merger events from the financial crisis and do not need to identify control firms. Instead, our causal analysis is a within-firm analysis where we compare the success of patents filed by the same firm in the same

[7] Anton *et al.* (2018) and López and Vives (2019) argue that overlapping ownership between rival firms on the one hand mitigates their R&D disincentives caused by the free-riding problems in the presence of technological spillover, but on the other hand softens product market competition, which in turn reduces these firm's R&D incentives. Shradha (2019) finds that for firms operating in industries with similar products, overlapping ownership does indeed lead to less R&D investment. In contrast, our study predicts and finds a positive relation between a downstream firm's R&D investment and its overlapping ownership with upstream firms that own complementary patents.

[8] Schmalz (2018) provides an updated review of the literature.

year and same patent class, but subject to different degrees of holdup alleviation due to changes in shareholder overlap with the upstream firm. We also address Yegen's (2019) concerns that the financial institution merger event could lack statistical power due to a rapid rebalancing of equity position by the new merged fund.

Last, we highlight empirical work that finds a complementarity between equity market development and the degree of patent innovation (Brown, Martinsson, and Petersen, 2013, 2017; Hsu, Tian, and Xu, 2014). Insofar as equity market development allows better internalization of holdup problems (through enhanced and adjustable *shareholder overlap*), this paper offers a deeper microeconomic interpretation rooted in the theory of the firm for the documented findings.

3 Measurement Issues and Sample Selection

3.1 Patent Holdup Identification

Empirical measurement of the holdup risk of a patent requires the identification of its complementary patents. Following Murray and Stern (2007) and Galasso and Schankerman (2015), we track complementary patents and their owners directly from the reference list of patent filings. By law, each newly filed patent must list prior art references (i.e., upstream patents) that are technologically related and material to the patentability of the new application. Although inventors have a duty of candor to disclose all material prior art, patent examiners in USPTO are officially responsible for constructing the list of references. According to Alcácer, Gittelman, and Sampat (2009), examiners insert at least one citation in 92% of patent applications, and examiner citations account for about 63% of all citations made by an average patent. Our analysis identifies potential patent holdup based on this list of prior art references and assumes that the list is exogenously determined by the technology to be patented. Indeed, the frequent addition of precursory patents by patent examiners suggests that the patent-filing firms have limited scope to manipulate the reference list.

Providing further support that citation links are useful in tracking down complementary patents, prior research (Galasso and Schankerman, 2015; Noel and Schankerman, 2013; Ziedonis, 2004) suggests that owners of upstream cited patents are reasonable proxies for the potential licensors of downstream citing patents. So-called patent consultants have occasionally disclosed that they screen the list of companies that cite their clients' patents to identify potential licensees (Ziedonis, 2004).[9] In fact, two U.S. inventors, Stephen K. Boyer and Alex Miller, were granted a patent (US6879990) in 2005 for proposing a systematic approach to identifying potential licensees from patent citation references.[10] Commenting on the strength of the citation measure, Galasso and Schankerman (2015) state that "*From an economic perspective, patent citations play two distinct roles: they indicate when a new invention builds on prior patents (and thus may need to license the upstream patent), and they identify prior art that circumscribes the property rights that can be claimed in the new patent.*" Following this line of literature and industry practice, our analysis uses patent citation links to upstream firms to track cumulativeness in innovation and to proxy for the potential patent holdup risk faced by a downstream firm.

We concede that our identification of holdup is imperfect and may sometimes produce incorrect results. For example, a citation link could identify a rival upstream patent for which the downstream patent is a substitute rather than complementary. In this case, there is no risk of holdup and potential underinvestment. Such mis-identified holdup cases can be expected to attenuate our parameter estimates, but should not per se generate false positive results. The supplementary evidence in Figure 1 on patent litigation risk between citation linked firm pairs and royalty payments by the downstream firms should reassure the reader that citation links identify a potential holdup situation.

3.2 Shareholder Overlap at the Patent and Firm Level

A key explanatory variable in our analysis is *shareholder overlap*, which we define as follows: Let $O(p)$ designate the downstream innovating firm owning patent p and $O(p_u)$ represent the upstream firm owning patent p_u. The *pairwise (institutional) shareholder overlap* between the downstream

[9] Ziedonis (2004) discusses three cases in her paper (Mogee Associates, InteCap, and Delphion). Ambercite, another intellectual property consulting company, advocated a similar approach in a recent internet posting (www.ambercite.com, 2014).

[10] They suggest creating a pool of associated patents from citation references of the target patents. Certain weighting scheme and ranking criteria are then applied to rank the owners of these associated patents and identify companies that are most likely to need a patent license from the target firms.

patent p and an upstream patent p_u is defined as

$$PSOL_{p,p_u} = \sum_i \min[w_{i,O(p)}, w_{i,O(p_u)}], \tag{1}$$

where $w_{i,O(p)}$ and $w_{i,O(p_u)}$ are the ownership share (relative to the total institutional ownership of the respective firm) of institutional investor i in firms $O(p)$ and $O(p_u)$, respectively. As an illustration, consider the following example: Two investors A and B, respectively, own 3% and 5% in the downstream firm $O(p)$, and 2% and 6% in the upstream firm $O(p_u)$, so that their combined shareholder overlap for the patent pair (p, p_u) amounts to $PSOL_{p,p_u} = min(3\%, 2\%) + min(5\%, 6\%) = 7\%$. We time-lag the ownership measurement by one year relative to the application year of patent p.[11]

The *patent-level shareholder overlap* (sol) is defined as the average of $PSOL_{p,p_u}$ over the N_u upstream patents of patent p, given by

$$sol_p = \sum_{u=1}^{N_u} \frac{1}{N_u} PSOL_{p,p_u} \ , \tag{2}$$

and the *firm-level shareholder overlap* (SOL) is obtained by averaging sol_p over all N_p patents filed by firm s in a given year, given by

$$SOL_s = \sum_{p=1}^{N_p} \frac{1}{N_p} sol_p = \sum_{p=1}^{N_p} \sum_{u=1}^{N_u} \frac{1}{N_p} \frac{1}{N_u} PSOL_{p,p_u} \ . \tag{3}$$

A limitation of our analysis is that due to data constraints we can measure ownership only for publicly listed firms, not for private firms. Neither are data on the portfolio holdings of private investors generally publicly available. As a result, we may underestimate the extent of shareholder overlap, especially when the proportion of privately owned upstream patents is large. This imprecise measure of shareholder overlap creates an attenuation bias in the OLS estimate of SOL. To mitigate this effect, we track the average share of privately owned upstream patents for each downstream firm s and include it as a control variable, denoted by $Private\ Patent\ Share_s$.

[11] Our evidence is qualitatively robust to alternative timing assumptions that assume a larger time delay of two or three years.

3.3 Patent Information

We collect patent and citation information from the data set provided by Kogan, Papanikolaou, Seru, and Stoffman (2017). The data set contains annual patent and citation information for patents granted over the period 1926–2010.[12] Following the existing literature (e.g., Aghion *et al.*, 2013; Acharya and Xu, 2017; Blanco and Wehrheim, 2017), we use the total number of a patent p's future citations ($cites_p$) from the patent filing year t to 2010 as our proxy for patent success. Forward citation count has been shown to correlate positively with the economic value of a patent (e.g., Harhoff, Narin, Scherer, and Vopel, 1999; Kogan *et al.*, 2017) and with firm value (e.g., Hall, Jaffe, and Trajtenberg, 2005; Farre-Mensa, Hegde, and Ljungqvist, 2019). In robustness checks, we also use the dollar value of a patent estimated by Kogan *et al.* (2017) as an alternative measure of patent success and find qualitatively similar results.[13]

Generally, a patent is not known to the public during its application stage until USPTO publishes it, typically 18 months after the filing date. For earlier patents (filed before November 29, 2000), patent applications are not published until after they are granted. According to Hall, Jaffe, and Trajtenberg (2001), it takes on average 18 months for a patent's application to be approved and about 95% of successful patent applications are granted within three years of application.

We aggregate the patent-level citation count $cites_p$ to the total number of future citations generated by the cohort of patents filed by firm s in year t, denoted by $CITES_{s,t}$. Self-citations are excluded. Following the convention in the innovation literature (e.g., Acharya and Xu, 2017), we set the citation count of a patent to zero when there is no citation information provided in the data. For firms without any patents, we set their total citation count to missing. We also examine the extensive margin of patent production $N_{s,t}$, defined as the number of patent filings by firm s in year t. The corresponding intensive margin is measured by the average citations per

[12] The data set is available at https://iu.app.box.com/patents. We thank Professor Noah Stoffman for making the data set available to us. According to the mapping procedures documented in Lerner and Seru (2017) and Kogan *et al.* (2017), patents are assigned to their ultimate parent companies in most cases in Kogan *et al.*'s patent and citation dataset.

[13] Although forward citation count is an indirect measure of patent success, it has the advantage that it is directly observable for a large number of firms with a long history. The measure used in Harhoff *et al.* (1999) is based on a survey conducted in 1999 and is available for only a small number of U.S. and German patents. The precision of the dollar values of patents estimated by Kogan *et al.* (2017) relies on the validity of the model assumptions they use to obtain the estimates. Among other things, they assume that investors have perfect knowledge about the market value of a patent before it is granted by USPTO. Any violation of the model assumptions can cause the estimates to deviate away from their true values.

patent $\overline{cites}_{s,t}$ (which equals the ratio of $CITES_{s,t}$ to $N_{s,t}$). Because most of these patent-related measures are highly skewed, we generally apply a log transformation $ln(1 + X)$ to obtain more normally distributed variables for the regression analysis.

We follow standard procedures to adjust for patent and citation truncation biases. First, because the patent data set only includes those patents that are eventually granted, we use only patent applications up to 2007 in our empirical analysis to allow for a three-year window of future citations up to 2010. Second, we control for year fixed effects in all regressions to account for the fact that earlier cohorts of patents have more time to be cited than later cohorts. Third, we adjust for patent citation count based on the shape of the citation-lag distribution suggested by Hall *et al.* (2001, 2005).[14] Fourth, we also perform our tests using simple (unweighted) patent counts (i.e., extensive margin reported in Section 5.1). Fifth, as a robustness check, we count only the citations received during the calendar year of the patent grant and three subsequent years (Lerner, Sørensen, and Strömberg, 2011). Note also that because expired patents do not create any holdup problems, we ignore upstream patents that have expired by the time the shareholder overlap measure is constructed.[15,16]

3.4 Ownership Data

We obtain the ownership data from the Refinitiv 13F database (formerly Thomson Reuters). The SEC requires all institutional organizations, companies, universities, etc., that exercise discretionary management of investment portfolios over $100 million in equity assets to report their holdings on a quarterly basis. All common stock positions greater than 10,000 shares or $200,000

[14]For example, for a chemical patent filed in 2000, we observe only 10 years of citations. According to Table 5 of Hall *et al.* (2001), for a typical chemical patent about 52.9% of the estimated total citations occur during the first 10 years. Therefore, we would divide the observed total by 0.529 to yield the truncation-adjusted total citations.

[15]According to USPTO, the 20-year protection period for utility patents starts from the grant date and ends 20 years after the patent application was first filed. The only exception applies to those patents that are filed before June 8, 1995; these patents have a protection period that is the greater of either the 20-year term discussed earlier or 17 years from the grant date (http://www.uspto.gov/web/offices/pac/mpep/mpep-2700.pdf).

[16]Our use of the terminology "upstream" and "downstream" firms follows from the prior literature (e.g., Galasso and Schankerman, 2010, 2015). In most cases, upstream (cited) and downstream (citing) patents can be identified clearly. In the case in which two patents cross-cite each other, the identification of upstream and downstream patents is ambiguous. We check and find no such cases in our sample. In our empirical analysis, the "upstream" and "downstream" patent-owning firms are identified at the patent level. Our firm-level analysis is predicated on the argument that all firms face a certain degree of patent holdup as long as they engage in cumulative innovation. Consequently, a firm's average shareholder overlap with its upstream patent-owning firms should attenuate the patent holdup problem.

must be reported. Aghion *et al.* (2013) show reporting inconsistencies in ownership data prior to 1991, so we use ownership data only from 1991 onwards.

We then combine the patent and citation data with institutional ownership data for publicly listed firms in the United States. The control variables, including the (log) total assets $ln(Assets_{s,t-1})$, cumulative R&D investment $ln(1+R\&D\ Stock_{s,t-1})$, capital intensity $ln(K/L_{s,t-1})$, and firm leverage ($Leverage_{s,t-1}$), are drawn from the Compustat database and are chosen based on the existing literature (e.g., Aghion *et al.*, 2013; Lin, Liu, and Manso, 2019). Following general practice in the finance literature (e.g., Bloom, Schakerman, and Van Reenen, 2013; and Koh and Reeb, 2015), we set R&D expenditure to zero if it is not reported in the Compustat database, and we include in our regression models a dummy variable of 1 for the firm-year observations with missing R&D data. We obtain qualitatively similar results if we drop the missing R&D values or interpolate their values for any gaps of no more than three years. Last, we exclude all firm-year observations with missing values for the explanatory or control variables. All explanatory variables are measured in a one-year lag relative to outcome variables. As a result, our final sample begins in 1991, which is the first year of the available ownership data, and stops in 2006, which is one year before the last year of available patent and citation data. The sample features $2,893$ U.S. publicly listed firms, with a total of $582,694$ patents and $18,763$ firm-years of patent production.

3.5 Summary Statistics

Institutional ownership in U.S. stocks has grown rapidly, from an average of 25% in 1991 to 49% in 2006. The corresponding share is considerably larger for patent-filing firms and rises from 41% in 1991 to 70.3% in 2006. Patent-filing firms tend to be larger, and institutional investors typically prefer large firms. Graphs A and B in Figure 2 depict the distributions of institutional ownership and firm-level shareholder overlap, respectively, for the period 1991–2006. Parallel to the rise in institutional ownership, the average firm-level shareholder overlap increases from 15.7% in 1991 to 22% in 2006. In our analysis, year fixed effects are included in all regressions to ensure that the documented shareholder overlap effect does not capture any parallel time trend in patent success. Cross-sectionally, shareholder overlap is positively related to institutional ownership in the downstream firm and even more strongly with its market capitalization, as shown in Figure

2, Graphs C and D. Shareholder overlap also varies substantially across firms with similar levels of institutional ownership and market capitalization. Such large heterogeneity in a firm's indirect control over complementary upstream patents via overlapping shareholders can plausibly condition patent holdup and determine a firm's long-run patent success.

Table 1, Panel A, reports the summary statistics of the 18,763 firm-year observations for the period 1991–2006. A median firm-year in our sample has about 4 $(= e^{1.609} - 1)$ patents and 49 $(= e^{3.912} - 1)$ (citation-lag adjusted) forward citations. The firm-level shareholder overlap (SOL) features an average of 17.2% with a standard deviation of 12%. The median institutional ownership (IO) is high at 49.9%. Detailed definitions of all variables are provided in the Internet Appendix, Table A1.

For the causal inference in Section 4, we use a subsample of firms held in the portfolios of merging financial institutions. The analysis here is on the patent level and involves $33,158$ patents filed by portfolio firms in the eight-year event window around the financial institution mergers. This event sample is summarized in Table 1, Panel B, and features change in predicted and realized patent-level shareholder overlap. The median number of forward citations of a patent in the event sample is 5.97 $(= e^{1.942} - 1)$. Next, we turn to this quasi-natural experiment.

4 Evidence from a Quasi-Natural Experiment

First, we report the effect of the quasi-natural experiment of financial institution mergers on both shareholder overlap and patent success. The literature (e.g., He and Huang, 2017; Holthausen, Leftwich, and Mayers, 1990; Keim and Madhavan, 1996) suggests that financial institutions often merge for reasons unrelated to the prospects of their portfolio holdings and that the acquiring firm typically keeps the target's portfolio holdings for an extended period, as documented in Lewellen and Lowry (2020). Therefore, if a downstream innovating firm and its upstream firm holding complementary patents are separately held by the two merging financial institutions before the merger, their shareholder overlap should increase right after the merger. Hence, the merger events of financial institutions create exogenous variation in shareholder overlap between two firms suitable for causal inference.

4.1 Event Sample Design

We form our event sample following a methodology similar to He and Huang (2017). Specifically, we collect all merger deals between any two 13F financial institutions (with SIC Codes 6000-6999) announced during the period 1991–2006 from the SDC database. We require that the merger target stops its 13F filings within 12 months of the merger announcement.

The merging of two financial institutions potentially creates a new ownership partition and therefore a new shareholder overlap. Formally, let $\{w^-_{e,i,s}\}$ denote the ownership of financial institution i in firm s just before the financial institution merger event e. If two institutions k and l merge (i.e., k acquires l), we define the merger-induced (predicted) new ownership partition as $\{w^+_{e,i,s}\}$, where

$$w^+_{e,i,s} = \begin{cases} w^-_{e,i,s} & \text{if } \; i \neq k \text{ and } i \neq l \\ w^-_{e,k,s} + w^-_{e,l,s} & \text{if } \; i = k \\ 0 & \text{if } \; i = l \end{cases} . \tag{4}$$

The *predicted change in pairwise shareholder overlap* (with respect to the merger event e) between any downstream patent p and its upstream patent p_u then follows as

$$\Delta PSOL^{\text{pred}}_{e,p,p_u} = \sum_i \min[w^+_{e,i,O(p)}, w^+_{e,i,O(p_u)}] - \sum_i \min[w^-_{e,i,O(p)}, w^-_{e,i,O(p_u)}] \geq 0, \tag{5}$$

where $O(p)$ and $O(p_u)$ denote the firms owning patents p and p_u, respectively. As the pre-event ownership partition $\{w^-_{e,i,s}\}$ is a subdivision of the post-event ownership partition $\{w^+_{e,i,s}\}$, it follows that the change in pairwise shareholder overlap in Eq. (5) is non-negative.

Analogous to Eq. (2), we define the *predicted change* in the *patent-level shareholder overlap* ($\Delta sol^{\text{pred}}_{e,p}$) as the equally weighted average of $\Delta PSOL^{\text{pred}}_{e,p,p_u}$ over the N_u upstream patents of patent p. Formally, we have

$$\Delta sol^{\text{pred}}_{e,p} = \sum_{u=1}^{N_u} \frac{1}{N_u} \Delta PSOL^{\text{pred}}_{e,p,p_u}. \tag{6}$$

Next, we define the sample $\mathcal{T}$ of treatment candidate patents, which become treated patents (i.e., subject to an exogenous shareholder overlap increase) if their filing occurs in or after the merger completion year. A triplet of a patent p, a (downstream) firm $O(p)$ owning it, and a merger event e is a treatment candidate ($\langle p, O(p), e\rangle \in \mathcal{T}$), if (i) the predicted change in the patent-level shareholder overlap is larger than threshold value of 2% (i.e. $\Delta sol^{\text{pred}}_{e,p} > 2\%$),[17] and (ii) the filing date of the patent falls within an eight-year event window that starts three years before the merger year and ends four years thereafter. For the calculation of the predicted change in shareholder overlap, we use the ownership information in the last quarter before the merger announcement.

For each treatment candidate patent $\langle p, O(p), e\rangle \in \mathcal{T}$, we identify up to two control patents $\langle p', O(p'), e\rangle \in \mathcal{C}$ such that (i) the firm owning the patent p' is a portfolio firm of at least one of the two merging financial institutions, (ii) the patents p and p' are filed in the same year, and (iii) the predicted change in the patent-level shareholder overlap under the financial institution merger is zero (i.e., $\Delta sol^{\text{pred}}_{e,p'} = 0$). Generally, we pick the two control patents that are most similar to the treatment candidate patent in terms of their shareholder overlap to upstream firms in the quarter just before the merger.[18] This procedure produces $11,112$ treatment candidate patents, $7,285$ treated patents, and $22,046$ control patents. In total, a sample of 50 financial institution merger events are used and documented in the Internet Appendix, Table A4.

The statistical power of the empirical design depends on the persistence of portfolio choices after the financial institution merger. We can measure both the *realized* pairwise shareholder overlap change $\Delta PSOL_{e,p,p_u}$ and the *realized* patent-level shareholder overlap $\Delta sol_{e,p}$ using the observed portfolio weights $\{w_{e,i,s}\}$ in the year of patent filing instead of the predicted weights $\{w^{+}_{e,i,s}\}$. In Table 2, Panel A, we regress the realized shareholder overlap changes on the predicted changes separately for the pre-merger period (i.e., patent filing years $k = -3, -2, -1$) and post-merger period (i.e., patent filing years $k = 0, +1, +2, +3, +4$). Each regression includes event-firm fixed effects, patent-class fixed effects (Hall, Jaffe, and Trajtenberg, 2001), and calendar-year fixed effects. The regressions show an economically and statistically strong relationship between predicted (i.e., merger-implied) and realized ownership overlap change for both $\Delta PSOL$ and Δsol in the post-merger period in Columns 2 and 4, respectively, but not for years prior to the merger year in Columns 1 and 3, respectively. The point estimate of 0.549 in Column 4 implies that a 1 percentage point increase in predicted patent-level shareholder overlap generates on

[17] Our results are also robust to other threshold values like 2.5%, 1.5%, and 1%. Using larger threhold values causes a significant decline in the sample size. For example, we lose over 50% of events if we use a 3% threshold and over 80% if we use a 5% threshold.

[18] We also check robustness to matching three (instead of two) control patents to any treatment candidate patent. The results are very similar.

average a 0.549 percentage point increase in the realized overlap over the entire post-merger period. We conclude that financial institution mergers provide sufficient statistical power to discriminate between treated patents, which experience a predictable (long-run) increase in shareholder overlap with upstream patent, and control patents, for which such a relationship is (by construction) absent.[19]

4.2 Patent-Level Evidence

We employ a difference-in-difference approach to compare the success of treatment candidate patents and control patents within the eight-year event window around the year of the merger event. For each treatment candidate patent p with respect to merger event e, we define a dummy

$$TreatC_{e,p} = \begin{cases} 1 & \text{if} \quad \langle p, O(p), e \rangle \in \mathcal{T} \\ 0 & \text{if} \quad \langle p, O(p), e \rangle \in \mathcal{C} \end{cases} . \tag{7}$$

A second dummy marks all sample patents, namely treatment candidates or control patents that have a patent filing year $t(p)$ equal to or later than the merger completion year $T(e)$, formally

$$Post\text{-}Merger_{e,p} = \begin{cases} 1 & \text{if} \quad t(p) \geq T(e) \\ 0 & \text{if} \quad t(p) < T(e) \end{cases} . \tag{8}$$

Treated patents are those that are treatment candidates ($TreatC_{e,p} = 1$) and are filed after the financial institution merger has been accomplished ($Post\text{-}Merger_{e,p} = 1$). Therefore, we identify the treatment effect by the interaction of both dummies in the following regression specification

$$\begin{aligned} Y_p \quad = \quad & \alpha_0 + \alpha_1 Post\text{-}Merger_{e,p} \times TreatC_{e,p} + \alpha_2 Post\text{-}Merger_{e,p} + \\ & + \alpha_3 TreatC_{e,p} + \mu_t + \delta_f + \omega_{e,O(p)} + \nu_{e,p}. \end{aligned} \tag{9}$$

The outcome variable Y_p denotes either patent shareholder overlap (sol_p) or the log forward citation count $ln(1 + cites_p)$ for a patent p. We include calendar year fixed effects μ_t for the patent filing year in the regression. Moreover, $\omega_{e,O(p)}$ denotes an event and firm fixed effect for the downstream

[19] This addresses Yegen's (2019) concerns that merger-induced shareholder overlap increases are too transitory to undertake a meaningful inference based on such events.

firm $O(p)$ owning patent p. Thus, our specification controls for unobserved firm heterogeneity that could influence the outcome variables. Finally, δ_f denotes patent class fixed effects. The patent class is based on the main technological categories developed by Hall, Jaffe, and Trajtenberg (2001). Finally, $\nu_{e,p}$ represents the error terms.

Table 2, Panel B, reports the result for Eq. (9). In Column 1, the point estimate of 0.018 for the interaction term $Post\text{-}Merger_{e,p} \times TreatC_{e,p}$ confirms that treated patents filed after the financial institution mergers indeed experience an economically significant increase in shareholder overlap (sol) at a magnitude of about 12.08% of its standard deviation. Column 2 measures the corresponding post-merger treatment effect on patent citations. The point estimate of 0.126 for the interacted term $Post\text{-}Merger \times TreatC_{e,p}$ indicates that treated patents experience a 12.6% increase in their forward patent citations after the merger—a difference that amounts to about 10% of the standard deviation of log patent citations [$ln(1 + cites)$]. Both the increase in shareholder overlap and the increase in log patent citations are statistically significant at the conventional 1% level. Combining both results, we conclude that a one-standard-deviation increase in shareholder overlap (sol) generates additional patent citation growth of approximately 79% of its standard deviation. Overall, the evidence from institution mergers points to an economically significant causal relationship between shareholder overlap and patent success.

We next run the following enhanced specification with interacted event-year fixed effects to understand the dynamics of shareholder overlap and patent citations around merger events:

$$\begin{aligned} Y_p \;=\; & \alpha_0 + \sum_{k=-2}^{4} \alpha_{1,k}\ EventYear_k \times TreatC_{e,p} + \\ & + \sum_{k=-2}^{4} \alpha_{2,k}\ EventYear_k + \alpha_3 TreatC_{e,p} + \mu_t + \delta_f + \omega_{e,O(p)} + \nu_{e,p}. \end{aligned} \tag{10}$$

We plot the estimated coefficients $\alpha_{1,k}$, with $k \in [-2, 4]$, in Figure 3. Panel A shows that the shareholder overlap of treatment candidate patents evolves in parallel to that of control patents in the period before financial institution merger completion ($k = -2, -1$). The difference in shareholder overlap between treatment and control patents jumps in the merger completion year ($k = 0$) and persists afterward. This confirms that the implied change in shareholder overlap (based on pre-merger institutional holdings) indeed predicts the post-merger shareholder overlap increase for treated patents. The high degree of persistence for this shareholder overlap increase supports the validity of the design.[20]

Figure 3, Panel B shows the corresponding evolution of the difference in patent citations. The citation counts of treatment candidate and control patents move in parallel in the pre-merger period up to the merger year ($k = -2, -1, 0$), but start to diverge thereafter. The delayed response of patent citations is not surprising as it takes time for more shareholder overlap to translate into more patent success. Overall, Figure 3 provides no indication that the parallel trend assumption is violated.

To further address the endogeneity issues, we perform a falsification test in which we replace the actual merger event year $T(e)$ by a pseudo event year $T(e)'$, which we arbitrarily set as the actual event year minus four years. If our results are driven by the characteristics of merging financial institutions instead of the merger itself, we should observe coefficients in the falsification test akin to those in the main experiment. We then carry out the same test procedure as before to examine whether the post-event treatment patents experience an increase in shareholder overlap with upstream firms and an increase in future citations. The regression results reported in Panel B of Table 2 show that post-event treatment patents do not feature any statistically significant differences in the levels of shareholder overlap $sol_{e,p}$ and patent success $[ln(1+cites_p)]$ than control patents.

5 Firm-Level Evidence on Holdup Attenuation

Next, we examine broader cross-sectional evidence consistent with holdup attenuation and enlarge the firm sample to all firms involved in patent production. We examine a variety of input and output variables of patent production and relate them to firm-level shareholder overlap with the relevant upstream firms. Section 5.1 focuses on a citation weighted output measure of patent success as used in the previous literature and its relationship to shareholder overlap, followed by two placebo tests showing that the correct identification of precursory upstream patents is crucial to finding any attenuation effect of shareholder overlap. Section 5.2 examines how input

[20] Our evidence on the persistence of shareholder overlap increase is consistent with the findings of Lewellen and Lowry (2020) and Azar et al. (2018).

measures of R&D investment relate to shareholder overlap. Furthermore, we decompose the institutional ownership of the downstream firm into a component contribution to institutional ownership overlap with the upstream firm and a residual component representing institutional ownership *per se*. Section 5.3 links institutional overlap to the likelihood of patent litigation risk.

5.1 Patent Success and Shareholder Overlap

Our baseline regression relates a firm's patent success [measured in log terms as $ln(1+CITES_{s,t})$] to shareholder overlap (at the end of period $t-1$) in the following linear regression

$$ln(1 + CITES_{s,t}) = \beta_0 + \beta_1 SOL_{s,t-1} + \beta_2 Controls_{s,t-1} + \epsilon_I + \mu_t + \eta_{s,t}, \tag{11}$$

where the coefficient of interest β_1 is predicted to be positive if the firm's shareholder overlap ($SOL_{s,t-1}$) with complementary upstream patent owners attenuates holdup. The baseline regression is estimated for the period 1991–2006. The citation count $CITES_{s,t}$ for patents filed by firm s in year t includes all future citations up to year 2010, which are adjusted for the shape of the citation-lag distribution following Hall *et al.* (2001, 2005). For the choice of control variables, we follow Aghion *et al.* (2013); and Lin, Liu, and Manso (2019) to include the (log) total assets $ln(Assets_{s,t-1})$, the cumulative R&D investment $ln(1 + R\&D\ Stock_{s,t-1})$, a measure of relative capital intensity $ln(K/L_{s,t-1})$, and firm leverage $leverage_{s,t-1}$. We also control for the share of private firms in the cited upstream firms, $Private\ Patent\ Share_{s,t-1}$, and include industry and year fixed effects ϵ_I and μ_t.

Table 3, Panel A, Columns 1–2 present the results with robust standard errors clustered at the firm level reported in parentheses. All regressions control for a full set of year dummies and industry dummies based on four-digit SIC codes. Column 2 also controls for firm fixed effects, using the Blundell, Griffith, and Van Reenen (1999) pre-sample mean scaling estimator.

The ordinary fixed effect estimator with firm dummies is inconsistent if the independent variables (such as SOL) are predetermined rather than strictly exogenous (Imbens and Wooldridge, 2007).[21] Blundell *et al.* (1999) propose a "pre-sample mean scaling" method to control for firm

[21] The asymptotic bias is especially large for samples with small T. Specifically, Imbens and Wooldridge (2007) show that under contemporaneous exogeneity the fixed effect estimator with firm dummies has the property: plim $\hat{\beta} = \beta + O(T^{-1})$.

fixed effects and show that this estimator remains consistent even with predetermined regressors. This approach essentially replaces firm dummies with the pre-sample mean of the dependent variable (measured at the firm level). To make sure our regression estimates are consistent, we follow this procedure and construct a 25-year pre-sample mean of $CITES_{s,t}$.[22] The same procedure is also employed by Blundell *et al.* (1999) to examine the relation between innovations and market shares, by Aghion *et al.* (2013) to examine the relation between innovations and institutional ownership, and by Blanco and Wehrheim (2017) to examine the relation between innovations and option trading.

The baseline regression in Column 1 shows that shareholder overlap represents a statistically and economically significant explanatory variable with the predicted positive coefficient. The coefficient remains highly significant in Column 2, where we control for firm fixed effects as suggested by Blundell *et al.* (1999). A point estimate of 3.234 for SOL implies that an increase in shareholder overlap by one standard deviation (or 0.120) increases patent success in terms of a firm's log patent citation [$ln(1+CITES)$] by 19% of its standard deviation (2.071) or 10% of its mean (3.948). This shows that shareholder overlap with upstream firms owning complementary patents correlates strongly with the patent success of the downstream firm — a finding that supports the holdup attenuation hypothesis.

To further probe a potential omitted variable bias, we conduct two placebo tests. In these tests, we replace the *true* shareholder overlap (SOL) with a *placebo* shareholder overlap ($SOL\_Placebo1$ or $SOL\_Placebo2$). For $SOL\_Placebo1$, we replace each cited upstream firm with a *similar* firm that is *not cited* by the downstream firm in the given patent application year. A placebo firm is chosen based on the criteria that it must have the same four-digit SIC codes as the true upstream firm and have the shortest Euclidean distance to the true upstream firm in terms of (log) firm asset size and (log) number of patents filed in the past five years. $SOL\_Placebo2$ is constructed similarly but the placebo firms are matched to the true upstream firms based on their technological proximity (i.e., the closeness in the distribution of their patents across various technology fields), as defined by Bloom *et al.* (2013).

[22] For firms with fewer than 25 years of pre-sample history, we use the maximum number of years available to calculate the pre-sample mean. We require firms to have at least one year of pre-sample history to be included in the sample. Using an alternative cutoff of 20, 15, or 10 years does not change our results qualitatively.

In Columns 3–4 of Panel A, we find that the two placebo measures of shareholder overlap do not feature any statistically significant correlation with patent success. If the positive SOL effect documented in the previous sections is driven by unobservable factors *unrelated to patent citation links*, such omitted variables should similarly lead to a positive relation between placebo shareholder overlap and patent success. Yet, we do not find such evidence for the two placebo measures of shareholder overlap, suggesting that omitted variable bias cannot explain our results.

We can also decompose the overall patent success into its intensive and extensive margin, as shareholder overlap can affect them differently. The intensive margin of patent success is captured by the average number of citations per patent, $\overline{cites}$. Again, we use the logarithmic transformation $ln(1 + \overline{cites}_{s,t})$ to obtain a suitable dependent variable for the linear regression

$$ln(1 + \overline{cites}_{s,t}) = \gamma_0 + \gamma_1 SOL_{s,t-1} + \gamma_2 Controls_{s,t-1} + \epsilon_I + \mu_t + \eta_{s,t}, \tag{12}$$

where $\gamma_1 > 0$ implies that shareholder overlap correlates with the greater long-run success of each patent filed. A positive value of γ_1 also points to ex-post patent value destruction if patent conflict is not attenuated through shareholder overlap. Table 3, Panel B, Columns 1–2 summarize the relationship between shareholder overlap and the intensive margin of patent success. The point estimate (1.132) in Column 2 implies that an increase in shareholder overlap by one standard deviation (or 0.12) corresponds to an increase in the average citation count per patent of about 12% (6%) of its standard deviation (mean) of 1.145 (2.385).

The analogous specification for the extensive margin uses the (log) number of granted patents [$ln(1 + N_{s,t})$] applied by firm s in year t as the dependent variable in the linear regression

$$ln(1 + N_{s,t}) = \psi_0 + \psi_1 SOL_{s,t-1} + \psi_2 Controls_{s,t-1} + \epsilon_I + \mu_t + \eta_{s,t}, \tag{13}$$

where the coefficient ψ_1 captures the relation between shareholder overlap ($SOL_{s,t}$) and the (log) number of granted patents. Column 4 again reports a positive point estimate given by $\widehat{\psi}_1 = 1.733$. A one-standard-deviation increase in SOL is associated with a 21% increase in the number of patents—suggesting an economically strong nexus between holdup attenuation and the number of successful patent filings.

Overall, the results suggest that holdup attenuation through shareholder overlap is associated with both more citations for each patent granted (i.e., the intensive margin of patent success) and the pursuit of more patents (i.e., the extensive margin of patent production). The latter effect is of particularly high economic significance, indicative of a severe underinvestment problem related to patent holdup in cumulative innovation processes.

5.2 R&D Investment and Shareholder Overlap

The holdup attenuation hypothesis implies that shareholder overlap should not only foster patent success, but also reduce ex-ante firm underinvestment in R&D. R&D expenditure is directly reported and thus provides a useful accounting statistic to assess firm-level inputs into the patent development process.

We regress a firm's R&D expenditure relative to assets ($R\&D\ Exp_{s,t}/Assets_{s,t}$) on its shareholder overlap ($SOL_{s,t-1}$) with relevant upstream firms owning complementary patents using the following linear specification

$$R\&D\ Exp_{s,t}/Assets_{s,t} = \kappa_0 + \kappa_1 SOL_{s,t-1} + \kappa_2 Controls_{s,t-1} + \epsilon_s + \mu_t + \eta_{s,t}, \tag{14}$$

where the control variables include the (log) total assets $ln(Assets_{s,t-1})$, relative capital intensity $ln(K/L_{s,t-1})$, firm leverage $leverage_{s,t-1}$, and $Private\ Patent\ Share_{s,t-1}$. We also control for firm and year fixed effects ϵ_s and μ_t. Table 4, Column 1, reports a statistically highly significant point estimate of 0.117 for shareholder overlap. An increase in shareholder overlap by one standard deviation (or 0.120) increases the R&D expenditure to asset ratio by roughly 7% of its standard deviation (0.213) or about 11% of its mean (0.123). This suggests that the holdup attenuation effect of shareholder overlap on R&D investment is economically important.

Previous research has argued that institutional ownership can *ceteris paribus* provide better long-term managerial incentives conducive to the pursuit of R&D (e.g., Aghion *et al.*, 2013). We therefore control for institutional ownership in Column 2, but find that the shareholder overlap variable (SOL) retains its economic and statistical significance, whereas the institutional ownership variable (IO) is statistically insignificant. To probe this issue further, we decompose institutional ownership into (i) ownership by overlapping institutional shareholders (IO^{SOL}) that contributes to shareholder overlap (i.e., the aggregate ownership of all shareholders i with

$\min[w_{i,O(p)}, w_{i,O(p_u)}] > 0$ for at least one downstream-upstream patent pair (p, p^u)); and (ii) residual non-overlapping institutional ownership (IO^{NOL}). Formally, for each downstream firm s in year t we have

$$IO_{s,t} = IO^{SOL}_{s,t} + IO^{NOL}_{s,t}. \tag{15}$$

By construction, IO^{SOL} strongly correlates with the shareholder overlap measure SOL, with a correlation of 0.53 during our sample period. If institutional ownership *per se* exerts a positive influence on R&D investment, we expect the same positive coefficient for both $IO^{SOL}_{s,t-1}$ and $IO^{NOL}_{s,t-1}$ in our regressions. Column 3 modifies the specification in Eq. (14) to include both overlapping institutional ownership $IO^{SOL}_{s,t-1}$ and non-overlapping institutional ownership $IO^{NOL}_{s.t-1}$ and reveals that the effect is significant only for overlapping institutional owners. Previous evidence in the literature of a beneficial governance effect of institutional ownership on firm innovation may therefore be spurious as it fails to separate institutional ownership from the correlated effect of shareholder overlap (Aghion *et al.*, 2013).

5.3 Litigation Risk and Shareholder Overlap

If shareholder overlap can indeed attenuate patent holdup, it should also attenuate patent conflicts mutating into costly patent litigation. Evidence for a negative relation between patent litigation risk and shareholder overlap is therefore evidence of the same governance channel operating through overlapping equity ownership. The previous literature (e.g., Gerakos and Xie, 2019; He and Huang, 2017; Newham *et al.*, 2019) finds some evidence that investors internalize conflicts among firms in their equity portfolios. We extend this work to patent litigation based on patent litigation data from Public Access to Court Electronic Records (PACER).

During the sample period, our data identify 3,202 patent litigation cases comprising 4,325 plaintiff-defendant firm pairs for which both plaintiff and defendant can be linked to Compustat.[23] If the same plaintiff and defendant are involved in multiple litigation cases in any given year, we consider them as one plaintiff-defendant firm pair (referred to as a litigation pair hereafter). We obtain a sample of 3,808 patent litigation pairs. We include a patent litigation pair in our regression

[23] We have more plaintiff-defendant firm pairs than litigation cases because a litigation case can consist of several plaintiffs or several defendants. For example, if a case has two plaintiffs and three defendants, this case generates six plaintiff-defendant firm pairs.

sample whenever the defendant firm cites a plaintiff's patent in one of its patent filings in the 10 years leading up to the lawsuit year. This is the case for 866 (or 22.7%) of the patent litigation pairs. As illustrated in Figure 1, intra-industry pairs of patent filing firms characterized by a citation link from the defendant to the plaintiff come with a 15 times higher bilateral litigation risk (i.e., an absolute risk of 0.223%) compared to intra-industry firm pairs without such a citation link for which the absolute risk is only 0.010%. This suggests that patent citation links are a highly pertinent marker of potential patent conflict and holdup.

Next, we show that shareholder overlap can attenuate the litigation risk implied by upstream citation links based on a matched firm sample. For each defendant in a litigation pair, we search for matching firms that also cite in their patent filings the same plaintiff firm during the same 10-year window, but are not sued by the plaintiff firm. The matching procedure selects up to two firms within the same industry (two-digit SIC) based on the Mahalanobis-distance (Bloom *et al.*, 2013) along with six firm characteristics, namely, log firm assets $[ln(Assets_{s,t-1})]$, log market capitalization $[ln(MktCap_{s,t-1})]$, Tobin's q ($Tobin\ Q_{s,t-1}$), log R&D expenditure $[ln(1 + R\&D\ Exp_{s,t-1})]$, the number of patent filings over the past five years ($Patent\ Stock_{s,t-1}$), and the previous year's stock return ($Past\ Return_{s,t-1}$). Our choice of firm characteristics here follows Cohen, Gurun, and Kominers (2018). The final matched sample consists of 579 litigated firms and 1,043 matched non-litigated firms.

We estimate the following logit model

$$Litigation_{s,m,t} = \lambda_0 + \lambda_1 PSOL_{s,m,t-1} + \lambda_2 Controls_{s,m,t-1} + \epsilon_m + \eta_{s,m,t}, \tag{16}$$

where $Litigation_{j,m,t}$ is a dummy variable with a value of one if firm s is subject to patent litigation in year t, and zero otherwise. For each matched firm group m, which combines a litigated firm and two non-litigated firms, we include a firm group fixed effect ϵ_m. Hence, we compare matched firms that share a patent citation link to the same upstream firm that litigates one firm but not the other two. In addition, lagged firm variables ($Controls_{s,m,t-1}$) seek to control for differences not captured by the matching procedure. The explanatory variable of interest is the *pairwise shareholder overlap* $PSOL_{s,m,t-1}$ of firm s with the common potential plaintiff firm. We estimate the model, either with or without controlling for firm characteristics.

Table 5, Panel A compares the litigated and non-litigated firms with respect to the six matched variables and the pairwise shareholder overlap ($PSOL$) with the plaintiff. The two samples feature no systematic differences with respect to the six matching variables, but pairwise shareholder overlap with the plaintiff firm is unconditionally smaller by 0.015 (or 8.3% of the standard deviation of 0.18) for the litigated firm sample. Panel B, Column 1(a) reports the baseline regression results without controls while, in Column 2(a), all control variables are in place. Columns 1(b) and 2(b), respectively, report the average marginal effect for the logit regression in their preceding columns.

The average marginal effect reported in Column 2(b) shows a decrease in the likelihood of litigation by 10.5% [$= -0.581 \times 0.18$)] for an increase in the pairwise shareholder overlap by one standard deviation (or 0.18). We conclude that shareholder overlap with a potential upstream plaintiff predicts a reduction in patent litigation risk by an economically significant magnitude. This finding is again consistent with the holdup attenuation hypothesis of shareholder overlap.

6 Transmission of Ownership Influence

Institutional shareholders are likely to differ in their incentives to resolve a potential patent holdup and their ability to organize and implement ownership influence. Section 6.1 segregates institutional investors by their shareholder type, and Section 6.2 explores whether the concentration of any given shareholder overlap matters for holdup attenuation.

6.1 Heterogeneity Among Overlapping Shareholders

To explore the role of shareholder type, we categorize institutional investors into (i) dedicated investors and (ii) non-dedicated investors based on a *combination* of portfolio concentration (proxied by the Herfindahl-Hirschman Index, HHI) and portfolio turnover (proxied by the churn ratio defined in Gaspar, Massa, and Matos, 2005). We also identify investors that cannot be categorized to either one of the two categories due to the lack of historical data. At the end of each year, we sort all institutional investors by the HHI (in descending order) and churn ratio (in ascending order). For those investors with necessary information to calculate the churn ratio and HHI, we mark those in the top 50% of both the HHI sort and the churn ratio sort (i.e., high concentration and low turnover) as dedicated investors and the remaining investors as non-dedicated investors.

We decompose the overall shareholder overlap into parts coming from either dedicated investors, non-dedicated institutional investors, or investors we cannot categorize, i.e.

$$SOL_{s,t-1} = SOL\_Ded_{s,t-1} + SOL\_NonDed_{s,t-1} + SOL\_Unknown, \quad (17)$$

and repeat the regressions in Table 3, Panel A, Column 2, with both disaggregated explanatory variables.

Table 6, Column 2, reports the results and confirms the hypothesis that dedicated (overlapping) investors matter the most for holdup attenuation. The shareholder overlap contributed by dedicated investors (SOL_Ded) features a coefficient of 9.768 compared to the baseline coefficient of 3.234 for all shareholder overlap (reported again in Column 1 of Table 6). We can reject the null hypothesis that dedicated and non-dedicated shareholder overlap make the same contribution to patent success measured in terms of future patent citations $[ln(1 + CITES_{s,t})]$.[24]

6.2 Concentration of Shareholder Overlap

Does the concentration of overlapping ownership among relatively few institutional investors limit free-riding and facilitate the coordination of investor influence? To address this question, we consider a downstream patent p filed by firm s in year t and a related upstream patent p_u owned by firm u. Let $i \in I_{(p,p_u),t-1}$ denote an overlapping investor, who at the end of time $t-1$ owns equity shares (relative to total institutional ownership) $w_{i,s}$ and $w_{i,u}$ in firms s and u, respectively. For a patent pair (p, p_u), we can define a Herfindahl-Hirschman Index ($hhi_{(p,p_u),t-1}$) based on the overlapping ownership shares $\varpi_i = \min[w_{i,s}, w_{i,u}]$ of all overlapping shareholders $i \in I_{(p,p_u),t-1}$. We further average this concentration measure $hhi_{(p,p_u),t-1}$ over all N_u upstream patents (p_u) related to patent p and, subsequently, over all N_p downstream patents (p) filed by firm s in year t to obtain an average Herfindahl-Hirschman Index ($SOL\_HHI_{s,t-1}$) of ownership concentration of overlapping shareholders, defined as

[24] How can long-term, dedicated investors influence corporate decisions? In a survey of institutional investors, McCahery *et al.* (2016) document that long-term, dedicated investors intervene more frequently than short-term investors. They do so mainly through private, behind-the-scene discussions with management and private meetings with corporate board members. In addition, they discipline management with threats of exit, which they view as a complement to direct intervention. Crane, Koch, and Michenaud (2019) also find evidence that institutional investors coordinate and vote together against low-quality management proposals to improve corporate governance of their portfolio firms.

$$SOL\_HHI_{s,t-1} = \sum_{p=1}^{N_p} \sum_{u=1}^{N_u} \frac{1}{N_p} \frac{1}{N_u} hhi_{(p,p_u),t-1}, \tag{18}$$

where ownership shares are measured at the end of year $t-1$. SOL_HHI describes the concentration of overlapping ownership stakes at the firm level and thus captures the coordination problem among overlapping shareholders.

Table 6, Column 3 includes SOL_HHI as a separate control variable. The estimated coefficient is positive and statistically highly significant—suggesting that the concentration of joint ownership shares by overlapping shareholders positively correlates with patent success beyond the shareholder overlap SOL itself. The coefficient estimate of 1.126 for SOL_HHI implies that an increase in the ownership concentration of shareholder overlap by one standard deviation (or 0.181) generates the same effect on patent success as raising SOL by 36.5% relative to its mean ($= [1.126 \times 0.181] \ / \ [3.247 \times 0.172]$). These estimates suggest that coordination problems among dispersed overlapping institutional investors represent an important impediment to the exercise of effective shareholder power. In contrast, the concentration of shareholder overlap among only a few investors appears to facilitate holdup attenuation.

7 Robustness Issues

We conduct several additional robustness checks in this section. The detailed evidence is documented in Table A3 of the Internet Appendix.

First, Bloom, *et al.* (2013) show two countervailing *R&D spillover* effects on a firm's innovation success: A positive effect due to technology spillover (from other firms that operate in similar technology fields) and a negative effect due to product market rivalry (from other firms that operate in similar product markets). In Internet Appendix, Table A3, Column 1 shows that even after accounting for these two factors, measured by $ln(SpillTech)$ and $ln(SpillSIC)$, the shareholder overlap effect remains quantitatively unchanged.

Second, as patent citation count is often perceived as a value signal, overlapping institutional shareholders may promote cross-citations among firms in which they also have a joint equity stake. To eliminate such spurious effects from our regression, we exclude all citations that come from the upstream firms cited in the patent filings of the downstream firm. Table A3, Column 2 repeats the baseline regression but uses this modified patent citation $ln(1 + CITES^F)$ as the dependent variable. The estimate for SOL is quantitatively similar to that of the baseline regression, suggesting that any potential bias arising from such citation manipulation is small.

Third, we use several alternative measures of firm innovation success to replace the citation-based measure of innovation success. These measures are (i) the dollar value of patents estimated by Kogan *et al.* (2017); (ii) the number of top 10% most-cited patents a firm has filed each year; and (iii) the number of patent filings each year that belong to patent classes in which a firm has never filed patents before. Table A3, Columns 3–5 show that shareholder overlap positively relates to these alternative measures. The results indicate that our findings are robust and not specific to the particular citation count variable used.

Fourth, we estimate an alternative regression specification using a negative binomial model with $CITES_{s,t}$ as the dependent variable. Column 6 shows that the SOL effect remains strong in this specification.

Fifth, in unreported results, we replace our baseline measure of shareholder overlap $SOL_{s,t-1}$, which is based on ownership stake at the end of year $t-1$, with $SOL_{s,t-2}$ or $SOL_{s,t-3}$, which are measured based on ownership stake at the end of year $t-2$ or $t-3$. The SOL estimate remains highly statistically and economically significant, albeit at a lesser magnitude.

8 Conclusion

According to Shaprio (2020), *"Patent holdup has proven one of the most controversial topics in innovation policy, in part because companies with a vested interest in denying its existence have spent tens of millions of dollars trying to debunk it. Notwithstanding a barrage of political and academic attacks, both the general theory of holdup and its practical application in patent law remain valid and pose significant concerns for patent policy."* As Shaprio concedes, a major research obstacle resides in the difficulty of identifying actual holdup situations in large firm samples. Our paper makes progress in this critical direction by using citation links from downstream patent filings to precursory patents, as first proposed by Galasso and Schankerman (2015).

We show that such patent citation links feature a high correlation with the probability of patent litigation, the number of licensing agreements, and the amount of royalty transfer between firms. We then use the citations links to construct patent-level and firm-level measures of the holdup-sensitive shareholder overlap between the downstream firm filing a new patent and upstream firm owning the cited precursory patent. From a property rights perspective of the firm, a downstream firm with a large holdup-sensitive shareholder overlap benefits from an extended firm boundary and faces reduced holdup risk.

The first part of our analysis provides evidence on a causal effect of holdup-sensitive shareholder overlap on the patent success of the downstream innovator. Following He and Huang (2017), we identify 50 financial institution mergers in the period 1991–2006 that generate an exogenous increase in shareholder overlap at the patent level. A difference in difference analysis shows that patents filed by a downstream firm and subject to potential holdup by a specific upstream firm become more successful after the fund company merger if the respective firm pair benefits from the merger-induced increase in their holdup-sensitive shareholder overlap. A falsification test shows that the differential effect hinges on using the correct merger year. Our within-firm, patent-level evidence addresses concerns that control firm matching can be difficult and flawed in the context of financial institution mergers (Lewellen and Lowry, 2020).

The full sample of U.S. (patent filing) listed firms in 1991–2006 with 18,763 firm-years reveals an economically and statistically significant relationship between a firm's patent success and the average shareholder overlap with firms controlling precursory patents. This strong relationship extends to both the extensive margin (patent count based) and the intensive margin (citation count based) of patent production. Placebo tests show that this positive relationship only exists if shareholder overlap is calculated for the correct firm pairs matching the patent citation link from the downstream to the upstream patent. We also document that shareholder overlap with upstream firms is an important covariate of R&D investment. Decomposing institutional ownership into a component delivering shareholder overlap and the residual component of (pure) institutional ownership *per se* shows that the former and not the latter matters as a positive covariate of a firm's R&D investment.

A third set of results concerns the transmission of ownership interests into firm outcomes. First, shareholder overlap coming from more dedicated investors tends to contribute more to the holdup attenuation—suggesting that the "extended boundary" of the innovating firm also depends on the types of institutional shareholders and its degree of "activism". Second, the ownership concentration of shareholder overlap matters independently of the overlap level, which suggests coordination and free-rider problems within a dispersed group of overlapping shareholders.

The holdup attenuating effect of shareholder overlap identified in this paper is only one facet of institutional ownership. We predict that more insights into its role will be obtained by a conditional analysis focusing on specific problems of interfirm coordination and conflict. Finally, our own identification of holdup risk through citation links could be refined in future research and possibly fine-tuned to the specific institutional and technological conditions found in each industry. Advances in the measurement of patent holdup promise a more informed public policy debate on how to render an economy increasingly dominated by tech firms both more innovative and more competitive.

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Table 1: Summary Statistics

Panel A reports summary statistics on the U.S. publically listed firm with patent filings in the period 1992–2006. Firm-level dependent variables are (i) $CITES_{s,t}$, the number of future citations received by the cohort of patents filed by firm s in year t; (ii) $N_{s,t}$, the number of patents filed by firm s in year t; (iii) $\overline{cites}_{s,t}$, the average future citation count per patent for the cohort of patents filed by firm s in year t; and (iv) $R\&D\ Exp_{s,t}/Asset_{s,t-1}$, the R&D expenditure to the total assets ratio. $SOL_{s,t-1}$ refers to the shareholder overlap for firm s in year $t-1$. We decompose $SOL_{s,t-1}$ into the shareholder overlap originating from dedicated investors ($SOL\_Ded_{s,t-1}$), that from non-dedicated investors ($SOL\_NonDed_{s,t-1}$), and that from investors that we cannot classify into either category due to the lack of historical data ($SOL\_Unknown_{s,t-1}$). $IO_{s,t-1}$, $IO^{SOL}_{s,t-1}$, and $IO^{NOL}_{s,t-1}$ represent the institutional ownership of, respectively, all shareholders, overlapping shareholders, and non-overlapping shareholders of firm s. $SOL\_HHI_{s,t-1}$ is the average Herfindahl-Hirschman Index of shareholder overlap for firm s. The control variables include log total assets [$ln(Assets_{s,t-1})$], log cumulative R&D investment [$ln(1+R\&D\ Stock_{s,t-1})$], log capital to labor ratio [$ln(K/L_{s,t-1})$], firm leverage ($Leverage_{s,t-1}$), and the average proportion of privately owned upstream patents ($Private\ Patent\ Share_{s,t-1}$). Panel B provides patent level summary statistics for the quasi-natural experiment of fund company mergers. For treatment candidate patents we calculated the realized and predicted change in pairwise shareholder overlap ($\Delta PSOL_{e,p,p_u}$, $\Delta PSOL^{\text{pred}}_{e,p,p_u}$) and the realized and predicted change in patent-level shareholder overlap ($\Delta sol_{e,p}$, $\Delta sol^{\text{pred}}_{e,p}$), respectively. We denote by sol_p and $ln(1+cites_p)$ the patent-level shareholder overlap, and the total (log) number of future citations received by patent p, respectively. Detailed definitions of the these variables are given in Table A1 in the Internet Appendix.

	Obs.	Mean	Median	S.D.	Min.	P25	P75	Max.
Panel A: Full Sample								
$ln(1+CITES)$	18,763	3.948	3.912	2.071	0.000	2.584	5.305	11.640
$ln(1+\overline{cites})$	18,763	2.385	2.455	1.145	0.000	1.702	3.127	6.643
$ln(1+N)$	18,763	1.966	1.609	1.342	0.693	0.693	2.639	8.395
$R\&D\ Exp/Assets$	18,763	0.123	0.061	0.213	0.000	0.014	0.151	7.478
SOL	18,763	0.172	0.164	0.120	0.000	0.077	0.254	0.727
SOL_Ded	18,763	0.003	0.001	0.007	0.000	0.000	0.003	0.173
SOL_NonDed	18,763	0.160	0.153	0.111	0.000	0.072	0.236	0.698
$SOL\_Unknown$	18,763	0.009	0.005	0.013	0.000	0.000	0.012	0.210
SOL_HHI	18,763	0.186	0.125	0.181	0.000	0.077	0.239	1.000
IO	18,763	0.482	0.499	0.267	0.000	0.254	0.695	1.000
IO^{SOL}	18,763	0.378	0.364	0.278	0.000	0.116	0.614	1.000
IO^{NOL}	18,763	0.100	0.037	0.158	−0.000	0.004	0.123	1.119
$ln(Assets)$	18,763	5.785	5.585	2.219	0.209	4.141	7.276	14.194
$ln(1+R\&D\ Stock)$	18,763	3.746	3.881	2.235	0.000	2.385	5.112	10.714
$ln(K/L)$	18,763	3.663	3.558	0.991	−2.492	3.045	4.207	9.957
$Leverage$	18,763	0.140	0.081	0.165	0.000	0.001	0.233	0.786
$Private\ Patent\ Share$	18,763	0.736	0.766	0.193	0.000	0.616	0.879	1.000
Panel B: Event Sample								
$\Delta PSOL$	11,112	−0.003	0.004	0.107	−0.514	−0.030	0.045	0.356
$\Delta PSOL^{\text{pred}}$	11,112	0.032	0.026	0.016	0.020	0.022	0.034	0.204
Δsol	20,856	0.010	0.010	0.118	−0.514	−0.037	0.074	0.570
Δsol^{pred}	20,856	0.030	0.025	0.013	0.020	0.022	0.032	0.204
$ln(1+cites)$	33,158	1.895	1.942	1.263	0.000	1.036	2.779	6.083
sol	33,158	0.253	0.248	0.149	0.000	0.134	0.361	0.743

Table 2: Patent-Level Evidence from A Quasi-Natural Experiment

We identify 50 merger deals between financial institutions that create an exogenous increase in shareholder overlap for patents in potential holdup situations. A patent p is defined as a treatment candidate patent ($TreatC_{e,p} = 1$) with respect to merger event e, if (i) its predicted change in the patent-level shareholder overlap ($\Delta sol^{\text{pred}}_{e,p}$) is larger than the threshold value of 2% and (ii) the filing date of the patent falls within an eight-year event window that starts three years before merger year and ends four years thereafter. For each treatment candidate patent p, we identify control patents p' such that (i) the firm owning the control patent p' is a portfolio firm of at least one of the two merging financial institutions, (ii) the patents p and p' are filed in the same year, and (iii) the predicted change in the patent-level shareholder overlap under the financial institution merger is zero. We select the two control patents (with $TreatC_{e,p'} = 0$) that are most similar to the treatment candidate patent in terms of their shareolder overlap to upstream firms in the quarter just before the merger. The dummy variable $\textit{Post-Merger}_{e,p}$ marks as 1 all patents filed on the merger event year and the four years thereafter ($k = 0, +1, +2, +3, +4$) and 0 otherwise ($k = -3, -2, -1$). Panel A shows that the predicted shareholder overlap changes explain realized shareholder overlap changes: We regress in Columns 1-2 the *realized* change in pairwise shareholder overlap ($\Delta PSOL_{e,p,p_u}$) onto its *predicted* value ($\Delta PSOL^{\text{pred}}_{e,p,p_u}$) for pre-merger patent filings ($\textit{Post-Merger}_{e,p}$=0) and post-merger patent filings ($\textit{Post-Merger}_{e,p}$=1), respectively. Columns 3-4 repeat this exercise for the *realized* change in patent-level shareholder ($\Delta sol_{e,p}$) and the *predicted* change ($\Delta sol^{\text{pred}}_{e,p}$). Panel B shows the diff-in-diff results for the natural experiment in Columns 1-2 and a falsification test in Columns 3-4. The dependent variables are, respectively, the patent-level shareholder overlap (sol_p) and the log future citation count [$ln(1 + cites_p)$] for patent p. For the falsification test we pick a pseudo event year for each financial institution merger, which is the actual merger year minus four years. All regressions control for interacted merger event-firm fixed effects, patent class fixed effects, and calendar year fixed effects. Robust standard errors are reported in parentheses, which are clustered at the merger event-firm level. Also reported are the total number of observations and the adjusted R-squared. ***, **, and * denote the 1%, 5%, and 10% significance level, respectively.

Panel A: Realized versus Predicted Shareholder Overlap for Treatment Candidate Patents

Dependent Variables:	$\Delta PSOL$		Δsol	
	Post-Merger=0	*Post-Merger*=1	*Post-Merger*=0	*Post-Merger*=1
	(1)	(2)	(3)	(4)
$\Delta PSOL^{\text{pred}}$	−0.064	0.319***		
	(0.136)	(0.110)		
Δsol^{pred}			0.167	0.549***
			(0.160)	(0.107)
Event × Firm FE	Yes	Yes	Yes	Yes
Patent Class FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	7,227	13,629	3,827	7,285
F-statistics	0.220	8.370	1.09	26.29
Adj. R^2	0.320	0.191	0.595	0.344

Panel B: Diff-in-Diff for Patent-Level Shareholder Overlap and Patent Success

	Natural Experiment		Falsification Test	
Dependent Variables:	*sol*	$ln(1 + cites)$	*sol*	$ln(1 + cites)$
	(1)	(2)	(3)	(4)
Post-Merger × *TreatC*	0.018***	0.126***	−0.008	−0.045
	(0.005)	(0.047)	(0.009)	(0.069)
TreatC	0.012**	−0.088**	0.016*	0.064
	(0.006)	(0.042)	(0.009)	(0.062)
Post-Merger	−0.013***	−0.002	−0.016**	−0.052
	(0.005)	(0.045)	(0.008)	(0.079)
Event × Firm FE	Yes	Yes	Yes	Yes
Patent Class FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	33,158	33,158	8,448	8,448
Adj. R^2	0.500	0.239	0.505	0.206

Table 3: Firm-Level Patent Success and Shareholder Overlap

Panel A reports firm-level OLS regressions of (overall) patent success $ln(1 + CITES_{s,t})$, i.e., the log number of future citations received by the cohort of patents filed by firm s in year t. The sample period is 1991–2006. The key variable of interest $SOL_{s,t-1}$ measures the lagged average shareholder ownership overlap at the end of year $t-1$ between the innovating firm s and its upstream firms owning complementary patents. The control variables include log total assets [$ln(Assets_{s,t-1})$], log cumulative R&D investment [$ln(1+R\&D\ Stock_{s,t-1})$], log capital to labor ratio [$ln(K/L_{s,t-1})$], leverage ($Leverage_{s,t-1}$), and the average proportion of privately owned upstream patents ($Private\ Patent\ Share_{s,t-1}$) for firm s in year $t-1$. Columns 3–4 report two placebo tests. For $SOL\_Placebo1$, we replace each cited upstream firm with a similar firm that is not cited by the downstream firm in the given patent application year. A placebo firm is chosen based on the criteria that it must have the same four-digit SIC codes as the true upstream firm and have the shortest Euclidean distance to the true upstream firm in terms of (log) firm asset size and (log) number of patents filed in the past five years. $SOL\_Placebo2$ is constructed similarly but the placebo firms are matched to the true upstream firms based on their technological proximity. Panel B decomposes patent success into its intensive margin $ln(1 + \overline{cites})$, i.e., the log average future citation count per patent for the cohort of patents filed by firm s in year t; and its extensive margin, $ln(1 + N_{s,t})$, i.e., the log number of successful patent applications filed by firm s in year t. All regressions control for a full set of year dummies and industry dummies based on four-digit SIC codes. Firm fixed effects are based on Blundell *et al.* (1999). Robust standard errors clustered at the firm level are reported in parentheses. Also reported are the total number of observations and the adjusted R-squared. ***, **, and * denote the 1%, 5%, and 10% significance level, respectively.

Panel A: Overall Patent Success

Dependent Variable:	$ln(1 + CITES)$			
	(1)	(2)	(3)	(4)
SOL	3.570***	3.234***		
	(0.210)	(0.206)		
$SOL\_Placebo1$			−0.069	
			(0.248)	
$SOL\_Placebo2$				−0.300
				(0.230)
Controls:				
$ln(Assets)$	0.100***	0.054**	0.172***	0.175***
	(0.022)	(0.021)	(0.022)	(0.021)
$ln(1 + R\&D\ Stock)$	0.425***	0.355***	0.370***	0.370***
	(0.022)	(0.022)	(0.022)	(0.022)
$ln(K/L)$	0.059**	0.076***	0.077***	0.077***
	(0.029)	(0.028)	(0.029)	(0.029)
$Leverage$	−0.425***	−0.369***	−0.539***	−0.542***
	(0.128)	(0.127)	(0.132)	(0.131)
$Private\ Patent\ Share$	0.108	0.011	−0.386***	−0.380***
	(0.105)	(0.103)	(0.103)	(0.103)
Year & Industry FE	Yes	Yes	Yes	Yes
Firm FE (BGV)	No	Yes	Yes	Yes
Observations	18,763	18,763	18,763	18,763
Adj. R^2	0.532	0.545	0.532	0.532

Panel B: Intensive and Extensive Margin of Patent Success

Dependent Variables:	$ln(1 + \overline{cites})$		$ln(1 + N)$	
	(1)	(2)	(3)	(4)
SOL	1.192***	1.132***	1.939***	1.733***
	(0.116)	(0.116)	(0.130)	(0.126)
Firm controls	Yes	Yes	Yes	Yes
Year & Industry FE	Yes	Yes	Yes	Yes
Firm FE (BGV)	No	Yes	No	Yes
Observations	18,763	18,763	18,763	18,763
Adj. R^2	0.427	0.428	0.629	0.657

Table 4: R&D Expenditure and Shareholder Overlap

Reported are OLS regressions of the R&D expenditure (relative to assets) for the sample period 1991–2006. $R\&D\ Exp_{s,t}/Assets_{s,t-1}$ denotes the R&D expenditure to the total firm assets ratio for firm s in year t. $SOL_{s,t-1}$ measures the average shareholder ownership overlap at the end of year $t-1$ between the innovating firm s and its upstream firms owning complementary patents. $IO_{s,t-1}$, $IO^{SOL}_{s,t-1}$, and $IO^{NOL}_{s,t-1}$ represent the institutional ownership of, respectively, all shareholders, overlapping shareholders, and non-overlapping shareholders in firm s at the end of year $t-1$. The control variables include log total assets $[ln(Assets_{s,t-1})]$, log capital to labor ratio $[ln(K/L_{s,t-1})]$, leverage $(Leverage_{s,t-1})$, and the average proportion of privately owned upstream patents $(Private\ Patent\ Share_{s,t-1})$ for firm s in year $t-1$. All regressions control for a full set of year dummies and firm dummies. Robust standard errors clustered at the firm level are reported in parentheses. Also reported are the total number of observations and the adjusted R-squared. ***, **, and * denote the 1%, 5%, and 10% significance level, respectively.

Dependent Variable:	*R&D Exp/Assets*		
	(1)	(2)	(3)
SOL	0.117***	0.115***	
	(0.022)	(0.022)	
IO		0.016	
		(0.016)	
IO^{SOL}			0.035**
			(0.015)
IO^{NOL}			0.008
			(0.014)
Controls:			
$ln(Assets)$	−0.104***	−0.105***	−0.103***
	(0.009)	(0.009)	(0.008)
$ln(K/L)$	0.007	0.008	0.007
	(0.006)	(0.006)	(0.006)
Leverage	0.006	0.006	0.005
	(0.018)	(0.018)	(0.018)
Private Patent Share	−0.007	−0.007	−0.015
	(0.015)	(0.015)	(0.016)
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Observations	18,763	18,763	18,763
Adj. R^2	0.565	0.565	0.564

Table 5: Litigation and Shareholder Overlap

We report logit regressions for the likelihood of being litigated for patent infringement. We construct a sample of litigated firms (defendants) subject to patent infringement lawsuits. To be included in the sample, the litigated firm must cite the plaintiff's patents in its own (downstream) patent filings at least once in the 10 years leading up to the patent lawsuit. For each defendant in a litigation pair, we search for matching firms that also cite in their patent filings the same plaintiff firm during the same 10-year window, but are not sued by the plaintiff firm. The matching procedure selects up to two firms within the same industry (two-digit SIC) based on the Mahalanobis-distance for six firm characteristics, namely, log firm assets [$ln(Assets_{s,t-1})$], log market capitalization [$ln(MktCap_{s,t-1})$], Tobin's q ($Tobin\ Q_{s,t-1}$), log of R&D expenditure [$ln(1 + R\&D\ Exp_{s,t-1})$], the number of patent filings over the past five years ($Patent\ Stock_{s,t-1}$), and last year's stock return ($Past\ Return_{s,t-1}$). Panel A reports the balance tests on the six matching firm characteristics and pairwise shareholder overlap ($PSOL_{s,t-1}$). Panel B reports the regression estimates for the Logit model in Columns 1(a) and 2(a) and their corresponding average marginal effect in Columns 1(b) and 2(b). All regressions include firm group dummies that identify a litigated firm and its two matched firms. Robust standard errors clustered at the firm group level are reported in parentheses. Also reported are the total number of observations and pseudo R-squared. ***, **, and * denote the 1%, 5%, and 10% significance level, respectively.

Panel A: Balance Tests

	Litigated Firms		Matched Firms		Difference
	Obs.	Mean	Obs.	Mean	(2)-(4)
	(1)	(2)	(3)	(4)	(5)
$PSOL$	579	0.232	1,043	0.247	-0.015^{***}
$ln(Assets)$	579	7.964	1,043	7.939	0.025
$ln(MktCap)$	579	15.213	1,043	15.243	−0.031
$Tobin\ Q$	579	0.361	1,043	0.353	0.007
$ln(1 + R\&D\ Exp)$	579	5.210	1,043	5.212	−0.002
$Patent\ Stock$	579	5.316	1,043	5.345	−0.030
$Past\ Return$	579	0.206	1,043	0.187	0.019

Panel B: Regression Results

Dependent Variable:	*Litigation (0/1)*			
	Logit Coefficient	Av. Marginal Effect	Logit Coefficient	Av. Marginal Effect
	(1a)	(1b)	(2a)	(2b)
$PSOL$	-2.027^{**}	-0.457^{**}	-2.600^{**}	-0.581^{**}
	(1.025)	(0.229)	(1.151)	(0.255)
$ln(Assets)$			0.160	0.036
			(0.260)	(0.058)
$ln(MktCap)$			0.258	0.058
			(0.214)	(0.048)
$Tobin\ Q$			0.997	0.223
			(0.910)	(0.203)
$ln(1 + R\&D\ Exp)$			0.106	0.024
			(0.204)	(0.046
$Patent\ Stock$			-0.393^{**}	-0.088^{**}
			(0.169)	(0.037
$Past\ Return$			0.204	0.046
			(0.289)	(0.065
Group fixed effects	Yes		Yes	
Observations	1,622		1,622	
Pseudo R^2	0.014		0.020	

Table 6: Heterogeneity and Concentration of Shareholder Overlap

Column 1 reproduces the baseline regression reported in Table 3, Panel A, Column 2. In Column 2, we decompose shareholder overlap ($SOL_{s,t-1}$) into the part originating from dedicated investors ($SOL\_Ded_{s,t-1}$), the part from non-dedicated investors ($SOL\_NonDed_{s,t-1}$), and the part from investors that we cannot classify into either category due to the lack of historical data ($SOL\_Unknown_{s,t-1}$). At the end of each year, we sort all institutional investors with necessary information by their portfolio concentration (in descending order) and churn ratio (in ascending order). We label investors in the top 50% of both the portfolio concentration sort and the churn ratio sort (i.e., high concentration and low turnover) as dedicated investors and the remaining investors as non-dedicated investors. Column 3 expands the baseline regression by including the average Herfindahl-Hirschman Index of the ownership concentration of overlapping shareholders, $SOL\_HHI_{s,t-1}$. The control variables include log total assets [$ln(Assets_{s,t-1})$], log cumulative R&D investment [$ln(1 + R\&D\ Stock_{s,t-1})$], log capital to labor ratio [$ln(K/L_{s,t-1})$], leverage ($Leverage_{s,t-1}$), and the average proportion of privately owned upstream patents ($Private\ Patent\ Share_{s,t-1}$) for firm s in year $t-1$. The sample period is 1991–2006. We report in the last row the p-value for the null hypothesis of equal coefficients in Column 2. All regressions control for a full set of year dummies and industry dummies based on four-digit SIC codes. Firm fixed effects are based on Blundell *et al.* (1999). Robust standard errors clustered at the firm level are reported in parentheses. Also reported are the total number of observations and the adjusted R-squared. ***, **, and * denote the 1%, 5%, and 10% significance level, respectively.

Dependent Variable:	$ln(1 + CITES)$		
	(1)	(2)	(3)
SOL	3.234***		3.247***
	(0.206)		(0.204)
SOL_Ded		9.523***	
		(2.733)	
SOL_NonDed		3.199***	
		(0.222)	
$SOL\_Unknown$		1.497	
		(1.303)	
SOL_HHI			1.126***
			(0.087)
Controls:			
$ln(Assets)$	0.054**	0.052**	0.106***
	(0.021)	(0.021)	(0.022)
$ln(1 + R\&D\ Stock)$	0.355***	0.353***	0.359***
	(0.022)	(0.022)	(0.022)
$ln(K/L)$	0.076***	0.076***	0.078***
	(0.028)	(0.028)	(0.028)
$Leverage$	−0.369***	−0.352***	−0.423***
	(0.127)	(0.127)	(0.126)
$Private\ Patent\ Share$	0.011	0.006	0.217**
	(0.103)	(0.103)	(0.105)
Year and Industry FE	Yes	Yes	Yes
Firm FE (BGV)	Yes	Yes	Yes
Observations	18,763	18,763	18,763
Adj. R^2	0.545	0.545	0.551
$H_0 : SOL\_Ded = SOL\_NonDed$		0.02	

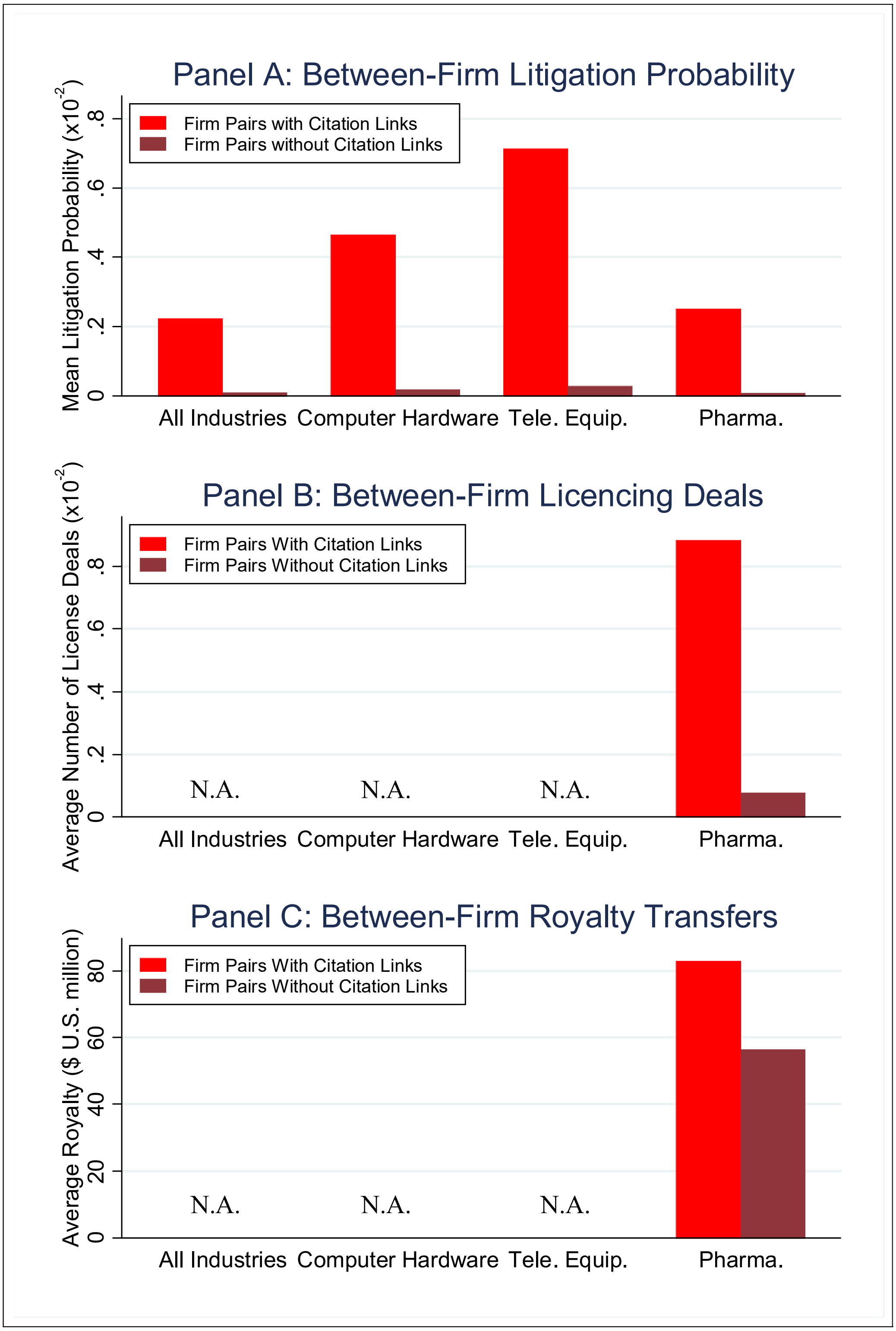

Figure 1: This figure compares the between-firm patent litigation probability (Panel A), the average number of licensing deals (Panel B), and royalty transfers (Panel C) for listed firm pairs with patent citation links and those without any citation link. The litigation cases are drawn from the PACER database. The licensing deals and royalty data are from the Cortellis database, which covers only pharmaceutical firms. For each year we form intra-industry firm pairs (based on the Fama-French 49 industry classification scheme) of all U.S. listed firms with at least one patent in the patent database and sort them into pairs with at least one patent citation link and pairs without any such link. In Panel A, the litigation probability is 0.223% for the pairs with patent citation links and 0.010% for the pairs without. The corresponding probabilities are 0.466% and 0.019% for the computer hardware sector, 0.715% and 0.030% for the telecommunication equipment sector, and 0.253% and 0.008% for the pharmaceuticals sector. In Panel B, the average number of patent licensing deals is 0.0089 for firm pairs with citation links and 0.0008 for the pairs without. In Panel C, conditional on firm pairs with licensing deals and royalty value available, the royalty value is USD 82.92 million for the pairs with citation links and USD 56.45 million for the pairs without. The label “N.A.” in Panels B and C indicates that the data are not available for the respective industries.

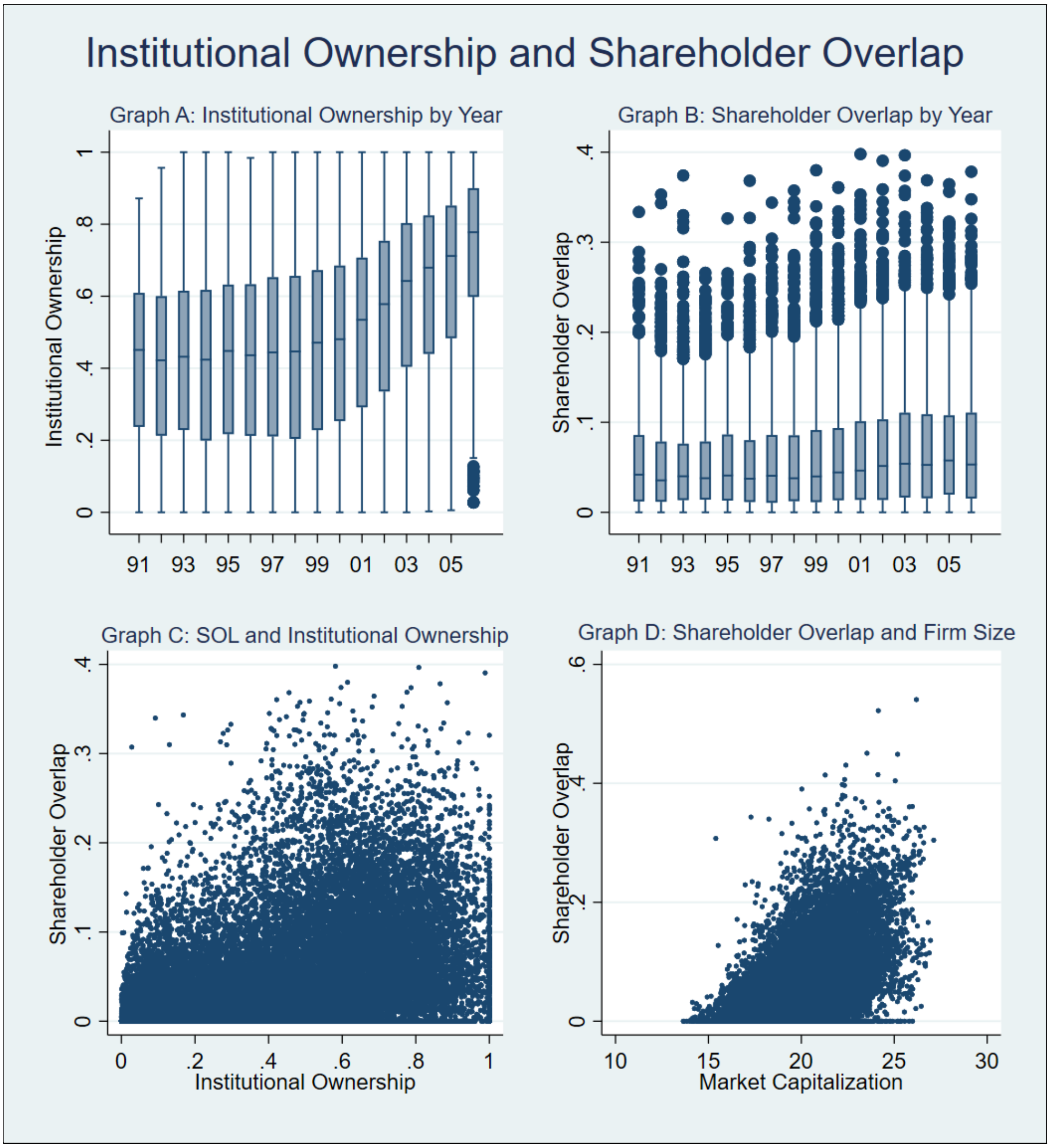

Figure 2: Institutional ownership and shareholder overlap. Graphs A and B are the box plots for the distribution of institutional ownership ($IO_{s,t}$) and shareholder overlap ($SOL_{s,t}$), respectively, by year from 1991 to 2006. The top, middle, and bottom values of each box represent the 75th, 50th, and 25th percentile of the distribution in the given year; the maximum and minimum of each vertical bar represent the upper and lower adjacent values, and the dots denote the observations outside the adjacent values. Graph C plots our sample along the dimension of shareholder overlap $SOL_{s,t}$ and institutional ownership $IO_{s,t}$, whereas Graph D plots along the dimension of shareholder overlap $SOL_{s,t}$ and firm size $ln(Assets_{s,t})$ for all firm-years.

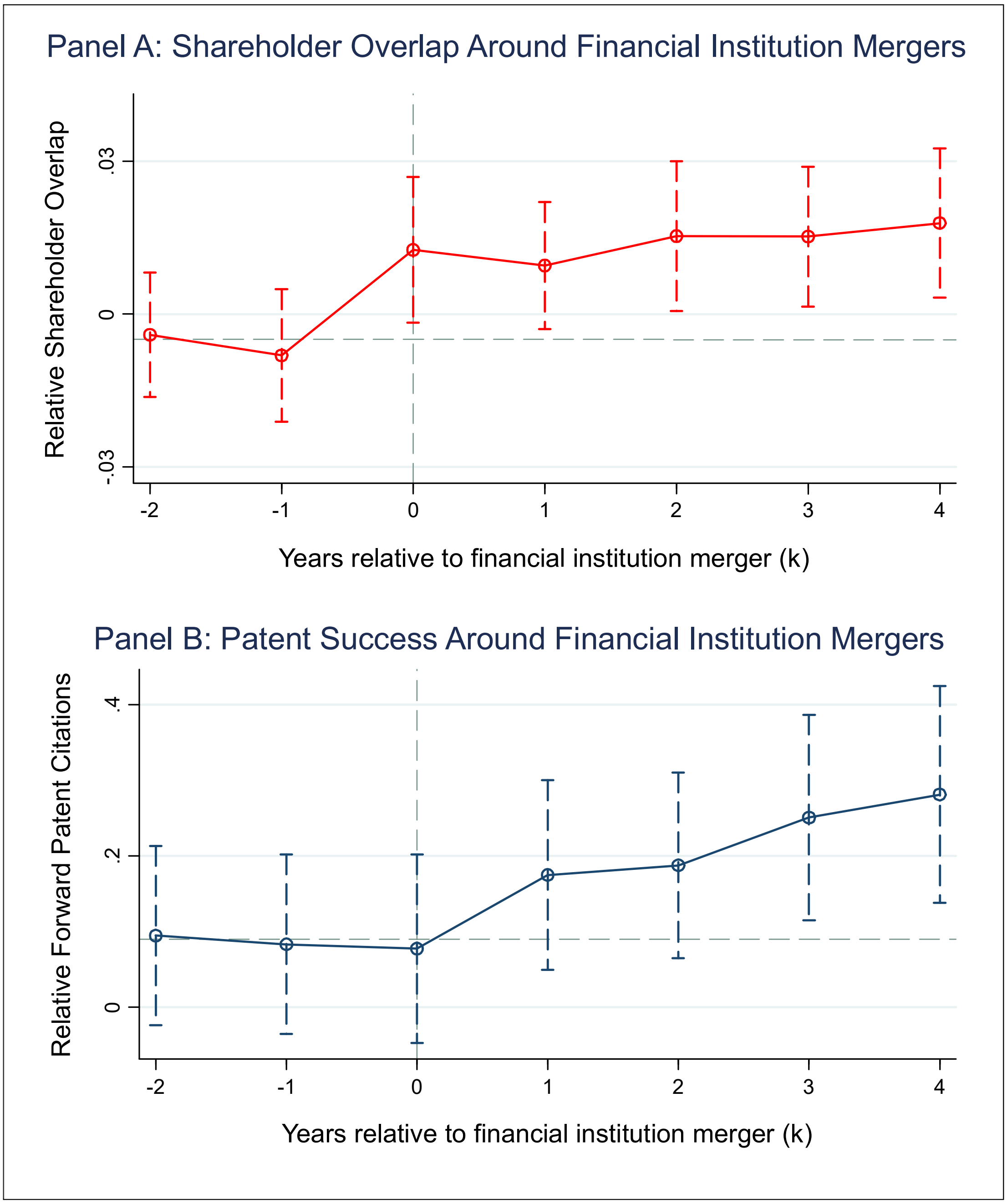

Figure 3: Panel A plots the evolution of patent shareholder overlap (sol_p) between the downstream patent p and all upstream patents p_u around financial institution mergers, and Panel B the corresponding dynamics of patent success based on (the log of) all cumulative forward patent citations $[ln(1 + cites_p)]$. Depicted in each case are the coefficient estimates $\widehat{\alpha}_{1,k}$ for the interaction term $EventYear_k \times TreatC_{e,p}$ in Eq. (10), where k denotes the number of years relative to the merger completion year. The vertical lines show 90% confidence intervals for the point estimate.

Internet Appendix

(Not for Journal Publication)

Does Shareholder Overlap Alleviate Patent Holdup?

Table A1: Variable Definitions

Variable	Description
$CITES_{s,t}$	Total future citation count for the cohort of patents filed by firm s in year t. Only those patents that are subsequently granted by USPTO are included in our sample. [Source: Kogan *et al.*, 2017; Hall *et al.*, 2001]
$N_{s,t}$	Number of patents filed by firm s in year t. Only those patents that are ultimately granted are included in our sample. [Source: Kogan *et al.*, 2017]
$\overline{cites}_{s,t}$	Average future citation count per patent for the cohort of patents filed by firm s in year t. [Source: Kogan *et al.*, 2017; Hall *et al.*, 2001]
$CITES^F_{s,t}$	Total filtered future citation count for the cohort of patents filed by firm s in year t. It removes from $CITES_{s,t}$ citations from the upstream firms cited in the patent filings of the downstream firm s in year t. [Source: Kogan *et al.*, 2017]
$R\&D\ Exp/Assets_{s,t}$	The ratio of $R\&D$ expenditure (XRD) in year t to total assets (AT) in year $t-1$. [Source: CRSP/Compustat Merged Database (CCM)]
$Patent\ \ Dollar\ Value_{s,t}$	The aggregate estimated market value of all patents filed by firm s in year t, measured in millions in 1982 dollars. [Source: Kogan *et al.*, 2017]
$N^{Top10\%}_{s,t}$	Number of patents filed by firm s in year t that belong to the top 10% most cited patents in their respective patent class. [Source: Our own calculation]
$N^{NewClass}_{s,t}$	Number of new class patents filed by firm s in year t. A new class patent in year t is defined as a patent belonging to a patent class in which the firm has never filed patents before. [Source: Our own calculation]
$Litigation_{s,m,t}$	A litigation dummy with a value of 1 if firm s is a treatment firm (which is subject to patent litigation in year t), and zero otherwise. Each treatment firm is matched to a control firm. The two firms form a matched firm pair m. [Source: LitAlert Database and Public Access to Court Electronic Records (PACER)]
$PSOL(p, p_u)$	Pairwise shareholder overlap $PSOL(p, p_u)$ between patent p's filing firm and the filing firm of its upstream patent p_u. It is measured according to Eq.(1). [Source: Kogan *et al.*, 2017; Thomson Reuters 13F]
$sol_{p,t}$	Shareholder overlap for patent p, filed in year t. It is the average of $PSOL(p, p_u)$ across all upstream patents (p_u, $u = 1, 2, .., N_u$) cited by patent p. In cases where multiple upstream patents are owned by the same firm, we aggregate their citation count and treat them as one single patent.[Source: Kogan *et al.*, 2017; Thomson Reuters 13F]
$cites_{p,t}$	Total number of future citations received by patent p, filed in year t. [Source: Kogan *et al.*, 2017]
$SOL_{s,t}$	Shareholder overlap for firm s in year t. It is the average of $sol_{p,t}$ across all patents p filed by firm s in year t. [Source: Kogan *et al.*, 2017; Thomson Reuters 13F]
$SOL\_Ded_{s,t}$	Shareholder overlap of dedicated investors for firm s in year t. It is the same as $SOL_{s,t}$ except that only the overlapping shares of dedicated investors are counted. At the end of each year, we sort all institutional investors by the HHI (in descending order) and churn ratio (in ascending order). We label investors in the top 50% of both the HHI sort and the churn ratio sort (i.e., high concentration and low turnover) as dedicated investors and the remaining investors as non-dedicated investors. The HHI is calculated as the sum of squares of each individual stock's weight in the investor's equity portfolio. The churn ratio for investor i in year t is calculated following Gaspar *et al.* (2005). [Source: Kogan *et al.*, 2017; CRSP and Thomson Reuters 13F]
$SOL\_NonDed_{s,t}$	Shareholder overlap of non-dedicated investors for firm s in year t. It is defined in an analogous way to $SOL\_Ded_{s,t}$. [Source: Kogan *et al.*, 2017; CRSP and Thomson Reuters 13F]
$SOL\_Uknown_{s,t}$	Shareholder overlap contributed by investors that cannot be categorized to dedicated investors or non-dedicated investors due to the lack of historical data. [Source: Kogan *et al.*, 2017; CRSP and Thomson Reuters 13F]
$SOL\_Placebo1_{s,t}$	First placebo shareholder overlap measure for firm s in year t. It is constructed in the same way as $SOL_{s,t}$ except that we replace every cited upstream firm with a *similar* firm that is *not* cited by the downstream firm s in the patent application year t. A placebo firm is chosen based on the criteria that it must have the same four-digit SIC code as the true upstream firm and that it has the shortest Euclidean distance from the upstream firm in terms of total assets and number of patents filed during $t-4$ to t. Both firm-level measures are log-transformed and scaled by their respective four-digit industry average. The Euclidean distance between firm $X = (X_{Assets}, X_{Patents})$ and $Y = (Y_{Assets}, Y_{Patents})$ is defined as $\sqrt{(X_{Assets} - Y_{Assets})^2 + (X_{Patents} - Y_{Patents})^2}$ [Source: Kogan *et al.*, 2017; CRSP/Compustat Merged Database (CCM)]

Table A1 Continued

Variable	Description
$SOL\_Placebo2_{s,t}$	Second placebo shareholder overlap measure for firm s in year t. It is constructed in the same way as $SOL\_Placebo1_{s,t}$ except that the placebo firms are matched to the true upstream firms based on their technological proximity. Following Bloom et al. (2013), we measure technological proximity between a true upstream firm u and a placebo firm x by $\frac{T_u T_x'}{\sqrt{T_u T_u'}\sqrt{T_x T_x'}}$, where $T_u = (T_{u,1}, ..., T_{u,K})$ and $T_x = (T_{x,1}, ..., T_{x,K})$. $T_{u,k}$ denotes the ratio of the number of patents filed by firm u in technological field $k \in [1, K]$ in the past three years to the total number of patents it filed during the same period. $T_{x,k}$ is defined analogously. The chosen placebo firm features the greatest value in the technological proximity measure among all firms not cited by the downstream firm in the given year. [Source: Kogan *et al.*, 2017]
$SOL\_HHI_{s,t}$	Average HHI of shareholder overlap concentration for firm s in year t. For each patent p filed by firm s in year t, we identify all the overlapping shareholders $i \in I_{p,pu}$ who have a joint equity stake in firm s and the firm owning the upstream patent p_u. We then calculate $hhi_{p,p_u,t}$ as the HHI based on the overlapping ownership share of each overlapping shareholder $i \in I_{p,pu}$, with the ownership measured at the end of year t. $WHHI_{s,t}$ is the average of $hhi_{p,p_u,t}$ across all patents p owned by firm s and their respective upstream patents p_u [Source: Kogan *et al.*, 2017; Thomson Reuters 13F]
$Private\ Patent\ Share_{s,t}$	Average proportion of private upstream patents for firm s in year t. For each patent p filed by firm s in year t, we calculate the share of privately owned upstream patents. We then average this private patent share across all patents filed by firm s in year t. [Source: Kogan *et al.*, 2017]
$IO_{s,t}$	Aggregate institutional ownership percentage of firm s in year t. It is the ratio of the number of shares held by institutional investors to the total number of shares outstanding for firm s at the end of year t. [Source: Thomson Reuters 13F and CCM]
$IO^{SOL}_{s,t}$	Overlapping institutional ownership of firm s in year t. For each patent application year t, we identify all *overlapping shareholders* that hold joint equity stakes in firm s and its upstream patent-owning firms. $IO^{SOL}_{s,t}$ measures the ratio of the total number of shares held by overlapping institutional shareholders to the total number of shares outstanding for firm s at the end of year t. [Source: CRSP and Thomson Reuters 13F]
$IO^{NOL}_{s,t}$	Non-overlapping institutional ownership of firm s in year t. For each patent application year t, we identify all *overlapping shareholders* that hold joint equity stakes in firm s and its upstream patent-owning firms. The remaining shareholders of firm s are identified as *non-overlapping shareholders*. $IO^{NOL}_{s,t}$ measures the ratio of the total number of shares held by non-overlapping institutional shareholders to the total number of shares outstanding for firm s at the end of year t. [Source: Thomson Reuters 13F and CCM]
$Assets_{s,t}$	Total assets value (AT) of firm s in year t, measured in USD millions. [Source: CCM]
$K/L_{s,t}$	Capital ($PPENT$) to labor (EMP) ratio for firm s in year t. [Source: CCM]
$R\&D\ Stock_{s,t}$	Cumulative R&D investment of firm s in year t. Following Hall *et al.* (2005), we measure $R\&D\ Stock_{s,t}$ as $R\&D\ Expenditure_{s,t} + 0.85R\&DStock_{s,t-1}$. [Source: CCM]
$Leverage_{s,t}$	Leverage ratio for firm s in year t, defined as long-term debt ($DLTT$) divided by total assets (AT). [Source: CCM]
$MktCap_{s,t}$	Market capitalization value for firm s in year t, which is measured at the end of the year in USD thousands. [Source: CRSP]
$Past\ Return_{s,t}$	The buy-and-hold stock return of firm s over the past 12 months before the patent litigation. [Source: CRSP]
$PatentStock_{s,t}$	Number of patents filed over the past five years. [Source: Our own calculation]
$TobinQ_{s,t}$	Tobin's q of firm s in year t, which is calculated as the sum of stockholders equity(SEQ), deferred tax and investment tax credit ($TXDITC$) minus preferred stock ($PSTKL$), then divided by the product of fiscal-year end stock price ($PRCC\_F$) and common shares outstanding ($CSHO$). [Source: CCM]
$SpillTech_{s,t}$	Technology (or knowledge) spillover from other firms for firm s in year t. It is the technological proximity-weighted sum of $R\&D\ Stock$ of all firms in year t except firm s. Technological proximity between firms m and s is defined by $\frac{T_m T_s'}{\sqrt{T_m T_m'}\sqrt{T_s T_s'}}$, where $T_m = (T_{m,1}, ..., T_{m,K})$ and $T_s = (T_{s,1}, ..., T_{s,K})$. $T_{m,k}$ denotes the ratio of the number of patents filed by firm m in technological class $k \in [1, K]$ over the whole sample period to the total number of patents it filed during the same period. $T_{s,k}$ is defined analogously. [Source: Kogan *et al.*, 2017; CCM]
$SpillSIC_{s,t}$	Product market rivalry effect of $R\&D$ for firm s in year t. It is the product market proximity-weighted sum of $R\&D\ Stock$ of all firms in year t except firm s. Product market proximity between firms m and s is defined by $\frac{X_m X_s'}{\sqrt{X_m X_m'}\sqrt{X_s X_s'}}$, where $X_m = (X_{m,1}, ..., X_{m,Q})$ and $X_s = (X_{s,1}, ..., X_{s,Q})$. $X_{m,q}$ denotes the share of firm m's sales in industry $q \in [1, Q]$ relative to its total sales during the year, averaged over the whole sample period. Industries are defined by four-digit SIC codes. $X_{s,q}$ is defined analogously. [Source: Kogan *et al.*, 2017; CCM]

Table A2: Additional Summary Statistics

We report additional summary statistics on variables used in Table A3. The sample is the same as in Table 1 and covers U.S. firms with patent filings in the period 1992–2007. The reported variables are log of a patent's dollar value [$ln(Patent\ Dollar\ Value_{s,t})$], log number of patents belonging to the top 10% most cited patents in their respective patent class [$ln(1 + N_{s,t}^{Top10\%})$], and log number of patents belonging to a new patent class in which a firm has never filed patents before [$ln(1 + N_{s,t}^{NewClass})$]. The variables $ln(SpillTECH_{s,t-1})$ and $ln(SpillSIC_{s,t-1})$ measure, respectively, the extent of technology spillover and product market rivalry effect of $R\&D$ for firm s in year $t-1$.

	Obs.	Mean	Median	S.D.	Min.	P25	P75	Max.
$ln(1 + CITES^F)$	18,763	3.904	3.870	2.054	0.000	2.549	5.249	11.565
$ln(Patent\ Dollar\ Value)$	18,763	2.481	2.087	2.731	−4.533	0.174	4.241	11.746
$ln(1 + N^{Top10\%})$	18,763	0.645	0.000	0.955	0.000	0.000	1.099	6.061
$ln(1 + N^{NewClass})$	18,763	0.571	0.693	0.647	0.000	0.000	1.099	4.220
$ln(SpillTECH)$	18,763	10.615	10.748	1.059	1.887	10.055	11.337	12.747
$ln(SpillSIC)$	18,608	8.626	9.035	2.301	−8.179	7.502	10.232	12.607

Table A3: Robustness

This table reports regression results on various robustness tests. Panel A reports robustness tests on model specifications. Additional explanatory variables, including technology spillover ($ln(SpillTech_{s,t-1})$), and the product market rivalry effect of R&D ($ln(SpillSIC_{s,t-1})$), are added to Columns 1–2. The dependent variable in Column 1 is $ln(1+CITES_{s,t})$. Column 2 uses a filtered citation measure, $ln(1+CITES^F_{s,t})$, as the dependent variable, which removes all citations coming from those upstream firms that firm s has cited in its patent filings in year t. Columns 3–5, respectively, measure firm innovation success by (i) the estimated log dollar value of a patent, $ln(Patent\ Dollar\ Value_{s,t})$,(ii) the number of top 10% most-cited patents a firm has filed each year, $ln(1+N^{Top10\%}_{s,t})$, and (iii) the number of patent filings each year that belong to the patent classes in which a firm has never filed patents before, $ln(1+N^{NewClass}_{s,t})$. Column 6 reports the estimation result using a negative binomial model. All regressions control for the same set of control variables and fixed effects as those included in Table 3, Panel A, Column 2. Robust standard errors clustered at the firm level are reported in parentheses. Also reported are the total number of observations and the adjusted R-squared. ***, **, and * denote the 1%, 5%, and 10% significance level, respectively. Detailed variable definitions are provided in Appendix A.

Dependent Variables:	$ln(1+CITES)$	$ln(1+CITES^F)$	$ln(Patent\ Dollar\ Value)$	$ln(1+N^{10\%})$	$ln(1+N^{NewClass})$	Neg. Binomial $CITES$
	(1)	(2)	(3)	(4)	(5)	(6)
SOL	3.266***	3.239***	4.178***	0.842***	0.410***	2.881***
	(0.210)	(0.209)	(0.230)	(0.099)	(0.066)	(0.306)
$ln(SpillTECH)$	0.104***	0.107***	0.187***	0.022	0.133***	0.103***
	(0.032)	(0.032)	(0.032)	(0.014)	(0.010)	(0.033)
$ln(SpillSIC)$	−0.039**	−0.039**	−0.042**	−0.026***	−0.005	−0.018
	(0.018)	(0.018)	(0.021)	(0.009)	(0.006)	(0.020)
Controls and FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,608	18,608	18,608	18,608	18,608	18,608
Adj. R^2	0.546	0.542	0.716	0.530	0.199	

Table A4: Financial Institution Mergers

This table lists the sample of 50 financial institution mergers that are used to define the event sample. The sample is restricted to the period 1992–2007 because of data limitations on the patent dataset. For each merger event, we report the announcement and completion date of the merger, the names of the acquirer and target financial institutions, the total market value of portfolio holdings of the acquirer and target in the calendar quarter-end before the merger announcement date, and the number of treatment candidate patents used in the experiment.

Announc. Date	Completion Date	Acquirer Name (mgrno)	Target Name (mgrno)	Combined Mkt. Cap ($ Billions)	No. of Treat. Cand. Patents
9-Sep-92	13-Jul-93	Bank of Boston (6000)	Multibank Financial Corp (59400)	4.94	302
14-Sep-92	30-Sep-93	Mellon Bank (55390)	Boston Company Inc (9750)	48.45	545
28-Jan-94	30-Sep-94	Bank of America (5980)	Continental Bank NA (21185)	8.06	12
6-Mar-94	30-Jun-94	First Union Corp (37700)	Evergreen Asset Mgmt (26100)	8.59	20
8-May-95	27-Dec-95	First Bank System (29285)	West One Bank Idaho (92150)	8.31	25
16-Jun-95	16-Jun-95	Tcw Group Inc (82690)	Continental Asset Mgmt (21000)	9.75	22
16-Jun-95	29-Feb-96	Mass Mutual Life Insur (54730)	Connecticut Mutual Life (20550)	4.32	10
19-Jun-95	2-Jan-96	First Union Corp (37700)	First Fidelity Bancorp. (29580)	13.94	92
28-Jun-95	3-Jan-96	Morgan Stanley Group (58950)	Miller Anderson & Sherrerd (57980)	16.61	113
10-Oct-95	30-Jun-96	Corestates Bank NA (21450)	Meridian Bancorp Inc. (56520)	5.83	5
18-Oct-95	30-Sep-96	Wells Fargo & Co (92035)	First Interstate Bancorp (29800)	21.74	34
13-Nov-95	11-Apr-96	Norwest Corpo (65850)	Victoria Bank & Trust (90560)	0.70	6
29-Nov-95	30-Jun-96	Travelers Inc (84900)	Aetna Life Ins & Annuity (520)	48.22	35
12-Dec-95	29-Jul-96	Bank of Boston (6000)	Baybanks Investment Mgmt (8220)	6.03	13
24-Jun-96	31-Oct-96	Morgan Stanley Group (58950)	Van Kampen Amer Capital (90450)	35.30	42
10-Jul-96	31-Oct-96	Chancellor Capital Mgmt (15110)	Lgt Asset Management Inc (39550)	21.22	55
6-Sep-96	12-Dec-96	First Union Corp (37700)	Keystone Invt Mgmt Co (49250)	23.18	36
20-Jan-97	20-May-97	Mellon Bank Corp (55390)	Ganz Capital Mgmt Inc (39800)	91.39	24
20-Mar-97	1-Aug-97	First Bank System (29285)	U S Bancorp (88855)	15.68	31
7-Apr-97	2-Sep-97	Bankers Trust NY Corp (7800)	Alex Brown Inc (10590)	100.04	149
11-Jun-97	30-Sep-97	Bank of New York (6890)	Signet Trust Company/Va (78987)	15.41	50
3-Oct-97	2-Jan-98	Northern Trust Corp (65260)	Anb Investment Mgmt & Tr (175)	56.51	470
5-Nov-97	1-Dec-97	Pimco Advisors LP (70470)	Oppenheimer & Co (67463)	60.92	399
1-Dec-97	31-Mar-98	Natl City Bank/Evansvlle (61236)	First of America Bank (29600)	1.55	157
8-Dec-97	30-Jun-98	First American Corp (29225)	Deposit Guaranty Natl Bank (22900)	1.17	168
11-Dec-97	1-Apr-98	Mellon Bank (55390)	Founders Asset Mgmt (38870)	120.87	508
6-Apr-98	8-Oct-98	Travelers Inc (84900)	Citicorp (16260)	121.60	604
13-Apr-98	30-Sep-98	Nationsbank Corp (62890)	Bankamerica Corp (5980)	69.77	557
30-Jun-98	31-Jul-98	United States Trust/NY (89310)	Wood Island Assocs (93600)	34.92	538
17-Mar-00	2-May-00	Northern Trust Co (65260)	Carl Domino Associates LP (23365)	90.10	12
10-Apr-00	31-Mar-01	Wells Fargo (65850)	First Security Corp/Utah (36920)	4.58	1386
17-May-00	9-Oct-00	M&T Capital Advr (67150)	Keystone Financial Inc. (49260)	1.75	1280
20-Jun-00	2-Oct-00	Axa Financial, Inc. (25610)	Sanford C.Bernstein (8650)	315.32	2300
13-Sep-00	31-Dec-00	JP Morgan & Co (58835)	Chase Manhattan Corp (15345)	186.24	359
2-Oct-00	1-Mar-01	Fleet Boston Corp (38260)	Summit Bank (82290)	50.04	46
16-Oct-00	26-Mar-01	Neuberger Berman (63050)	Fasciano, Michael (27190)	39.46	28
20-Oct-00	23-Apr-01	Federated Investors (27330)	Edgemont Asset Mgmt (24450)	19.64	28
23-Oct-00	12-Dec-00	New York Life Insurance (63830)	Towneley Capital Mgmt (84500)	9.28	15
25-Oct-00	10-Apr-01	Franklin Resources Inc (39300)	Fiduciary Trust Co (28060)	87.85	168
3-Apr-01	30-Aug-01	American Intl Group Inc (2470)	American General Corp (2340)	20.94	12
16-Apr-01	4-Sep-01	First Union Corp, NC (37700)	Wachovia Corp, NC (91000)	64.59	5
26-Apr-01	30-Sep-01	Mellon Bank NA (55390)	Standish, Ayer & Wood (80730)	165.21	13
22-Nov-02	17-Jan-03	Wells Fargo (65850)	Montgomery Asset Mgmt (58670)	39.03	18
2-Dec-02	31-Dec-02	Neuberger Berman (63050)	Libertyview Capital Mgmt (50805)	28.59	18
26-Aug-03	30-Sep-03	Wells Fargo (65850)	Benson Associates (8287)	48.46	22
27-Oct-03	1-Apr-04	Bank of America (62890)	Fleet Boston Corp (38260)	118.44	181
14-Jan-04	1-Jul-04	JP Morgan Chase & Co (58835)	Bank One Corp (5955)	129.51	129
23-Jan-04	1-Jul-04	Regions Financial Corp (72860)	Union Planters Bank, NA (53135)	2.40	24
26-May-04	3-Jan-05	Wells Fargo (65850)	Strong Capital Mgmt (82100)	72.95	43
21-Jun-04	1-Nov-04	Wachovia Corp (37700)	Southtrust Asset Mgmt (80000)	62.40	29